Benefit-Cost Technical Manual

Methods and User Guide

This technical manual describes the sources, assumptions, and computational methods used in the Washington State Institute for Public Policy's benefit-cost model. This document is periodically updated; it incorporates the latest revisions as of the date below.

Many WSIPP employees, both current and former, contributed to the information contained in this Benefit-Cost Technical Manual. For further information on the methods described in this report, contact Stephanie Lee at slee@wsipp.wa.gov or (360) 586-3951.

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The Washington State legislature created the Washington State Institute for Public Policy (WSIPP) in 1983. WSIPP is governed by a Board of Directors that represents the legislature, the governor, and public universities. The Board guides the development of all WSIPP activities. WSIPP's mission is to carry out practical, non-partisan research—at the direction of the legislature or the Board of Directors—on issues of importance to Washington State.

The legislature and the Board of Directors authorized WSIPP to receive outside funding for this ongoing work; the MacArthur Foundation and the Pew Charitable Trusts have helped the legislature support a large proportion of the work since 2009.

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Chapter 1: Overview of the Benefit-Cost Approach and Model

This Benefit-Cost Technical Manual describes the latest version of the Washington State Institute for Public Policy (WSIPP) benefit-cost model. WSIPP built its first model in 1997 to estimate the economic value of programs that reduce crime. Later, as WSIPP received additional and varied assignments from the Washington legislature, the benefit-cost model was revised and expanded to cover additional public policy outcomes. The model described here reflects our current approach to computing benefits and costs for a wide array of outcomes and contains several enhancements over earlier versions. Our ongoing goal is to provide Washington policymakers with better "bottom-line" estimates each successive legislative session.

The Washington State legislature often directs WSIPP to update and extend its review of the benefits and costs of programs and policies to improve public outcomes. For example, typical legislative language directs WSIPP to "calculate the return on investment to taxpayers from evidence-based prevention and intervention programs and policies."[1] Specifically, the legislature or the WSIPP Board of Directors has asked WSIPP to identify public policies that have been shown to improve the following broad outcomes of public interest:

- Crime
- K–12 education
- Child maltreatment
- Substance abuse
- Mental health
- Public health
- Public assistance
- Employment and workforce development
- Health care
- General prevention

Publications on these topics can be found on the WSIPP website: http://www.wsipp.wa.gov. A principal objective of WSIPP's model is to produce a "What Works?" list of public policy options available to the Washington State legislature and to rank the list by estimates of return on investment. The ranked list can then help policymakers choose a portfolio of public policies that are evidence-based and have a high likelihood of producing more benefits than costs. For example, if a public policy objective is to reduce crime, then a portfolio of evidence-based policies can be selected from the list—prevention policies, juvenile justice policies, and adult corrections policies—that together can improve the chance that crime is reduced and taxpayer money is used efficiently.

Our analytical goal for each evidence-based investment option we analyze is to deliver to the legislature two benefit-cost measures: an expected return on investment and, given the risk, the odds that the investment will at least break even. We then make results of these individual analyses available for inclusion in "investment portfolio" scenarios. There are four basic steps to the analysis.

1. **What Works?** First, we conduct systematic reviews of the research literature to identify policies and programs that demonstrate an ability to improve the outcomes. In Chapters 2 and 3, we describe the methods we use to identify, screen, and code research studies; the meta-analytic approach we use to estimate the effectiveness of policy options to achieve outcomes; and the procedures we use to compute monetizable units of change. The objective of the first step is to draw statistical conclusions about what works—and what does not—to achieve improvements in the outcomes, along with an estimate of the statistical error involved.
2. **What Makes Economic Sense?** The second basic step involves applying economic calculations to put a monetary value on the improved outcomes (from the first step). Once monetized, the estimated benefits are then compared to the costs of programs to arrive at a set of economic bottom lines for the investments. Chapter 4 describes the processes we use to monetize the outcomes.
3. **How Risky Are the Estimates?** Part of the process of estimating a return on investment involves assessing the riskiness of the estimates. Any rigorous modeling process, such as the one described here, involves many individual estimates and assumptions. Almost every step involves at least some level of uncertainty. Chapter 6 describes the "Monte Carlo" approach we use to model this risk. The objective of the risk analysis is to access the odds that an individual return on investment estimate may offer the legislature the wrong advice. For example, if we

[1] E.g., Laws of 2009, Ch. 564, § 610 (4).

conclude that, on average, an investment in program XYZ has a ratio of three dollars of benefits for each dollar of cost, what are the odds, given the risk in this estimate, that the program will generate at least one dollar of benefits for each dollar of cost?

4. **How Can a Portfolio of Evidence-Based Programs and Policies Change Statewide Outcomes?** Finally, the benefit-cost model also allows the user to combine policy options together into a portfolio. Much like the concept of an investment portfolio, this tool allows the user to pick and choose different policy options and project the combined impact of those options on statewide costs, benefits, and outcomes. Chapter 7 describes the inputs and outputs for the portfolio analysis.

1.1 Overview of the Model

WSIPP's benefit-cost model is an integrated set of estimates and computational routines designed to produce four related benefit-cost summary statistics: net present value, benefit-to-cost ratio, internal rate of return on investment, and measure of risk associated with these bottom-line estimates. In simplest form, the model implements a standard economic calculation of the expected worth of an investment by computing the net present value of a stream of estimated benefits and costs that occur over time, as described with equation 1.1.

$$(1.1)\quad NPV_{tage} = \sum_{y=tage}^{N} \frac{Q_y \times P_y - C_y}{(1+Dis)^y}$$

In this basic model, the net present value, *NPV,* of a program is the quantity of the outcomes achieved by the program or policy, *Q,* in year *y,* times the price per unit of the outcome, *P,* in year *y*, minus the cost of producing the outcome, *C*, in year *y*. The lifecycle of each of these values is measured from the average age of the person who is treated, *tage,* and runs over the number of years into the future over which they are evaluated, *N*. The future values are expressed in present value terms after applying a discount rate, *Dis*.

The first term in the numerator of equation 1.1, Q_y, is the estimated number of outcome "units" in year *y* produced by the program or policy. The procedures we use to develop estimates of Q_y are described in Chapters 2 and 3. In Chapter 4 we describe the various methods we use to estimate the price term, P_y, in equation 1.1. In Chapter 6, we describe the Monte Carlo simulation procedures we employ to estimate the risk and uncertainty in the single-point net present value estimates.

Rearranging terms in equation 1.1, a benefit-to-cost ratio, *B/C,* can be computed with:

$$(1.2)\quad \frac{B}{C} = \sum_{y=tage}^{N} \frac{Q_y \times P_y}{(1+Dis)^y} \Bigg/ \sum_{y=tage}^{N} \frac{C_y}{(1+Dis)^y}$$

Additionally, since the model keeps track of the estimated annual cash flows of benefits and costs of a program, an internal rate of return on investment can be computed. The internal rate of return is the discount rate, in equation 1.1, which results in a zero net present value. In computations, the internal rate of return is calculated using Microsoft Excel's© IRR function. For some cash flow series, internal rates of return cannot be calculated.

1.2 General Approach and Characteristics of WSIPP's Benefit-Cost Modeling Process

There are several features that are central to WSIPP's benefit-cost modeling approach.

Internal Consistency of Estimates. Because WSIPP's model is used to evaluate the benefits and costs of a wide range of public policies that affect many different outcomes, a key modeling goal is internal consistency. Any complex investment analysis, whether geared toward private sector or public sector investments, involves many estimates and uncertainties. Across all the outcomes and programs we consider, we attempt to be as internally consistent as possible. That is, within each topic area, our bottom-line estimates are developed so that a net present value for one program can be compared directly to that of another program. This is in contrast to the way most benefit-cost analyses are done, where one study conducts an economic analysis for one program and then another study performs a different benefit-cost analysis for another program. By adopting one modeling approach to assess all decisions, on the other hand, the consistency of results is enhanced, thereby enabling apples-to-apples benefit-to-cost comparisons.

Meta-Analytic Strategy. The first step in our benefit-cost modeling strategy produces estimates of policies and programs that have been shown to improve particular outcomes. We carefully analyze all high-quality studies from the United States and elsewhere to identify well-researched interventions that achieve positive outcomes (as well as those that do not). We look for research studies with strong, credible evaluation designs, and we ignore studies with weak research methods. Our empirical approach follows a meta-analytic framework to assess systematically all relevant evaluations we can locate on a given topic. By including all of the studies in a meta-analysis, we are, in effect, making a statement about the average effectiveness of a particular topic. For example, in deciding whether the program Functional Family Therapy works to reduce crime, we do not rely on just one evaluation of the program. Rather, we compute a meta-analytic average effect from all of the credible studies we find of Functional Family Therapy.

Long-Run Benefits and Costs. We include estimates of the long-term benefits and costs of programs and policies. In most cases, this involves WSIPP projections into the future. Projections are necessary, because most of the evidence about programs comes from evaluations with relatively short follow-up periods. It is rare to find longitudinal program evaluations. This problem, of course, is not unique to public programs. Most private investment decisions are based on past performance and future results are projected by entrepreneurs or investment advisors based on certain assumptions. We adopt that investment approach in this model. We forecast, using a consistent and empirically based framework, the long-term benefits and costs of programs and policies. We then assess the riskiness of the projections.

Sums of Benefits. Many evaluations of programs and policies measure multiple outcomes. In most cases, we sum the per-participant benefits across multiple outcomes to draw a comprehensive conclusion about the total benefits to society. However, some categories of benefits draw from the same ultimate monetary source. For example, high school graduation and standardized test scores are two outcomes that may both be measured by a program evaluation. We have methods to monetize both outcomes, but improvements in either lead to increased earnings in the labor market. To avoid "double-counting," rather than summing the benefits from both high school graduation and standardized test scores, we include the benefits from the outcome that produces greater benefits in the *average* case but do not include benefits from the other outcome(s).

Risk. Any tabulation of benefits and costs necessarily involves uncertainty and some degree of speculation about future performance. This is expected in any investment analysis. Therefore, it is important to understand how conclusions might change when assumptions are altered. To assess risk, we perform a Monte Carlo simulation technique in which we vary the key factors in our calculations. The purpose of the risk analysis is to determine the odds that a particular approach will at least break-even. That is, we are interested in the expected rate of return on investment for any program, but we also want to calculate the odds that a particular program will not break even. This type of risk analysis is used by many businesses in investment decision making; we employ the same tools to test the riskiness of the public sector options considered in this report.

Four Perspectives on Benefits and Costs. We present these monetary estimates from four distinct perspectives: the benefits that accrue solely to program participants, those received by taxpayers, other measurable (non-participant and non-taxpayer) monetary benefits, and other indirect benefits.

The sum of these four perspectives provides a "total Washington" view on whether a program produces benefits that exceed costs. Restricting the focus solely to the taxpayer perspective can also be useful for certain fiscal analyses and state budget preparation.

For example, we estimate the long-term labor market benefits that accrue directly to the participants in a successful early childhood education program. Higher levels of education also lead to indirect societal benefits; a better-educated workforce improves the economy more generally. As we show in this analysis, there is also evidence that a successful early childhood education program produces lower long-term crime rates and, thus, generates benefits to non-participants by lowering the amount of money that taxpayers have to spend on the criminal justice system. Lower crime also reduces the amount of costs that crime victims would otherwise have to bear. Thus, we provide estimates for each of the four perspectives: program participants, non-participants as taxpayers, non-participants in other non-taxpayer roles, and indirect societal benefits.

The Model's Expandability. The state of research-based knowledge is continually expanding. More is known today than ten years ago on the relative effectiveness of prevention and intervention programs and more will be known in the future. We built this benefit-cost model so that it can be expanded to incorporate this evolving state of evidence. Similar to an investment analyst's model used to update quarterly earnings-per-share estimates of private investments, this model is designed to be updated regularly as new and better information becomes available. This design feature allows increasingly refined estimates of the economic bottom lines for public programs, and will supply government decision makers with the latest information on how taxpayers can get better returns on their dollars. In addition, the model is designed in a modular fashion, such that new topic areas other than those listed on page 5 can be added to the analysis in a way consistent with the topics already assigned.

"Linking" Outcomes. In addition to examining the impacts of a program on directly measured outcomes, we estimate the benefits of indirectly measured outcomes. From our meta-analytic review of the evaluation literature, we establish a causal effect of the program on directly measured outcomes (e.g., crime). Other bodies of research, however, measure causal relationships between two outcomes (e.g., high school graduation and crime). Using the same meta-analytic approach, we take advantage of this research and empirically estimate the causal "links" between two outcomes. The monetization of indirectly measured outcomes becomes especially important in conducting benefit-cost analysis when not all of the impacts of a program are directly measured in the studies. Furthermore, measuring linked outcomes allows us to estimate the longer-term effects of programs when evaluations typically measure shorter-term outcomes.

1.3 Peer Review of the WSIPP Benefit-Cost Model

WSIPP has had external reviewers examine our work and provide feedback on our methods. In addition, we have had invitations in recent years to publish our work in several journals; thus, our benefit-cost model has been reviewed indirectly by journal editors.[2]

With assistance from the Pew Charitable Trusts (Pew) and the MacArthur Foundation, WSIPP's benefit-cost model is being implemented in 13 states as part of the Pew-MacArthur Results First Initiative.[3] As part of our work with these organizations, the benefit-cost model has been reviewed twice in the past three years by an independent team assembled by Pew. Most recently, the benefit-cost model was reviewed in 2012 by the following:

- R. Kirk Jonas: Director, Office of Research Compliance and Integrity, University of Richmond, Virginia; Chair, Institutional Review Board, University of Richmond, Virginia
- Lynn Karoly: Senior Economist and Director, Office of Research Quality Assurance, RAND Corporation
- Steven Raphael: Professor of Public Policy, Goldman School of Public Policy, University of California-Berkeley
- David Weimer: Professor of Public Affairs and Political Science, Robert M. La Follette School of Public Affairs, University of Wisconsin-Madison

The benefit-cost model was also reviewed in 2010 by David Weimer, Lynn Karoly, and additionally, Mike Wilson, Economist, Oregon Criminal Justice Commission.

In 2011, 2012, and 2013, Pew hosted annual meetings with the states involved in the Pew-MacArthur Results First Initiative. There were approximately 50-70 participants in attendance at each of the annual meetings. During this time, WSIPP received questions, comments, and criticisms on our technical and non-technical aspects of our methods, software, and policy scenarios.

Lastly, Pew has two technical assistance consultants responsible for learning the benefit-cost model in order to assist the 13 states in implementing the model. The technical assistance consultants, Steve Lize and Mike Wilson, have been using the benefit-cost model since 2011 and 2010, respectively. The technical assistance consultants continually provide feedback on our approach.

1.4 Updates to the Current Methods

The list that follows displays the major changes to the model structure and computational methods since the last publication of this Benefit-Cost Technical Manual in April 2012. In the benefit-cost model, we added:

- Capacity to sub-divide taxpayer benefits into state, local, and federal sources (inputs and data sources are described in Chapters 4.2, 4.3, 4.7, and 4.10).
- Ability to combine the expected results of any programs/policies in the benefit-cost model into an "investment portfolio;" users can project scenarios of expected long-term benefits, costs, and outcomes (described in Chapter 7).
- New taxpayer benefit breakouts by source allow users to access long-term benefits to taxpayers according to the "budget area" from which they originate (criminal justice, K–12 education, child welfare, health care, public assistance, and taxes raised from increased earnings of state residents).
- Capacity to apply an empirically derived, state-specific multiplier to expected earnings over time (described in Chapter 4.1).
- Capacity to add new, state-specific crime populations rather than overwriting previously defined populations (described in Chapter 4.2).

[2] See: (a) Drake, E. (2012). Reducing crime and criminal justice costs: Washington State's evolving research approach. *Justice Research and Policy,* 14(1), (b) Drake, E., Aos, S., & Miller. M. (2009). Evidence-based public policy options to reduce crime and criminal justice costs: Implications in Washington State. *Victims & Offenders: An International Journal of Evidence-based Research, Policy, and Practice*, 4(2). (c) Lee, S., Drake, E., Pennucci, A., Bjornstad, G., & Edovald. T. (2012). Economic evaluation of early childhood education in a policy context. *Journal of Children's Services*, 7(1), 53-63.
[3] See: http://www.pewstates.org/projects/pew-macarthur-results-first-initiative-328069

- Ability to use meta-analytic results from elasticity-based prison-crime and police-crime research literatures (described in the October 2013 WSIPP report on prison and policing).

Our methods have also been updated in the following ways:

- To avoid double-counting benefits, rather than taking a weighted average of multiple pathways that lead to a source of benefits (e.g., high school graduation and standardized test scores that both lead to earnings), we now select the single outcome that leads to the largest monetary benefits and deactivate the other pathways.
- We added an empirically-derived multiplier for the economic externalities of education-related human capital outcomes (described in Chapter 4.7).

Chapter 2: Methods Used to Estimate Effect Sizes and Standard Errors

As outlined in Chapter 1, the WSIPP model is an integrated set of estimates and computational routines designed to produce internally consistent benefit-to-cost estimates for a variety of public policies and programs. The model implements a standard economic calculation of the expected worth of an investment by computing the net present value of a stream of estimated benefits and costs that occur over time, as described with equation 2.1.

$$(2.1) \quad NPV_{tage} = \sum_{y=tage}^{N} \frac{Q_y \times P_y - C_y}{(1+Dis)^y}$$

In this basic model, the net present value, NPV, of a program is the quantity of the outcomes produced by the program or policy, Q, in year y, times the price per unit of the outcome, P, in year y, minus the cost of producing the outcome, C, in year y. The lifecycle of each of these values is measured from the average age of the person treated, $tage$ and runs over the number of years into the future over which they are evaluated, N. The future values are expressed in present value terms after applying a discount rate, Dis.

The first term in the numerator of equation 2.1, Q_y, is the estimated number of outcome "units" in year y produced by the program or policy. The procedures used to develop estimates of Q_y are described in Chapters 2 and 3. In Chapter 4 we describe the various methods we use to estimate the price term, P_y, in equation 2.1.

This Chapter describes the process we use to estimate effect sizes—one central element of Q_y, in equation 2.2.

2.1 Meta-Analytic Procedures to Compute Effect Sizes and Standard Errors

To estimate the effects of programs and policies on outcomes, we employ statistical procedures researchers have developed to facilitate systematic reviews of evaluation evidence. This set of procedures is called "meta-analysis" and we use that methodology in this study.[4]

Study Selection and Coding Criteria

A meta-analysis is only as good as the selection and coding criteria used to conduct the study.[5] Following are the key choices we made and implemented in recent WSIPP reports.

Study Selection. We use four primary means to locate studies for meta-analysis of programs: (1) we consult the bibliographies of systematic and narrative reviews of the research literature in the various topic areas; (2) we examine the citations in the individual studies themselves; (3) we conduct independent literature searches of research databases using search engines such as Google, Proquest, Ebsco, ERIC, PubMed, and SAGE; and (4) we contact authors of primary research to learn about ongoing or unpublished evaluation work. As we will describe, the most important criteria for inclusion in our study is that an evaluation must either have a control or comparison group, or use advanced statistical methods to control for unobserved variables or reverse causality. Therefore, after first identifying all possible studies via these search methods, we attempt to determine whether the study was an outcome evaluation that had a comparison group or included these advanced statistical methods. We also determine if each study used outcome measures that were standardized or well-validated. If a study meets these criteria, we then secure a paper copy of the study for our review.

Peer-Reviewed and Other Studies. We examine all evaluation studies we can locate with these search procedures. Many of these studies are published in peer-reviewed academic journals while others are from reports obtained from government agencies or independent evaluation contractors. It is important to include non-peer reviewed studies, because it has been suggested that peer-reviewed publications may be biased to show positive program effects. Therefore, our meta-analysis includes all available studies that meet our other criteria, regardless of published source.

Control and Comparison Group Studies. Our analysis only includes studies that have a control or comparison group (or use sophisticated statistical methods to infer causality from the results). That is, we do not include studies with a single-group, pre-post research design. This choice is made because it is only through rigorous comparison group studies that we can reliably estimate causal relationships.

[4] In general, we follow the meta-analytic methods described in: Lipsey, M. W. & Wilson, D. (2001). *Practical meta-analysis*. Thousand Oaks, CA: Sage Publications.

[5] All studies used in the meta-analyses for individual programs and policies are identified in the detailed results documented in WSIPP reports, found on the WSIPP website: http://www.wsipp.wa.gov. Many other studies were reviewed, but did not meet the criteria set for this analysis.

Exclusion of Studies of Program Completers Only. We do not include a study in our meta-analytic review if the treatment group is made up solely of program completers. We adopted this rule because there are too many significant unobserved self-selection factors that distinguish a program completer from a program dropout, and these unobserved factors are likely to significantly bias estimated treatment effects. Some studies of program completers, however, also contain information on program dropouts in addition to a comparison group. In these situations, we include the study if sufficient information is provided to allow us to reconstruct an intent-to-treat group that includes both completers and non-completers, or if the demonstrated rate of program non-completion is very small. In these cases, the study still needs to meet the other inclusion requirements listed here.

Random Assignment and Quasi-Experiments. Random assignment studies are preferred for inclusion in our review, but we also include non-randomly assigned comparison groups. We only include quasi-experimental studies if sufficient information is provided to demonstrate comparability between the treatment and comparison groups on important pre-existing conditions such as age, gender, and pre-treatment characteristics such as test scores or level of functioning.

Enough Information to Calculate an Effect Size. Following the statistical procedures in Lipsey and Wilson,[6] a study has to provide the necessary information to calculate an effect size. If the necessary information is not provided, and we are unable to obtain the necessary information directly from the study's author(s), the study is not included in our review.

Mean-Difference Effect Sizes. For this study, we code mean-difference effect sizes following the procedures in Lipsey and Wilson.[7] For dichotomous measures, we use the D-cox transformation to approximate the mean difference effect size, as described in Sánchez-Meca, Marín-Martínez, and Chacón-Moscoso.[8] We chose to use the mean-difference effect size rather than the odds ratio effect size because we frequently code both dichotomous and continuous outcomes (odds ratio effect sizes could also be used with appropriate transformations).

Multivariate Results Preferred. Some studies present two types of analyses: raw outcomes that are not adjusted for covariates such as age, gender, or pre-intervention characteristics; and those that are adjusted with multivariate statistical methods. In these situations, we code the adjusted outcomes and use test statistics from the regression to calculate an effect size.

Outcome Measures of Interest. Our primary outcomes of interest include standardized, validated measurements. A list of the outcomes coded in the program areas are listed in published WSIPP reports. Where possible, our model estimates monetary values for the outcomes. At this time, however, we are not able to monetize all of these outcomes.

Averaging Effect Sizes for Similar Outcomes. Some studies report similar outcomes: e.g., arrest and incarceration, or reading test scores from different standardized assessments. In such cases, we meta-analyze the similar measures and use the combined effect size in the meta-analysis for that program. As a result, each study sample coded in this analysis is associated with a single effect size for a given outcome.

Longest Follow-Up Periods. When a study presents outcomes with varying follow-up periods, we generally code the effect size for the longest follow-up period. The longest follow-up period allows us to gain the most insight into the long-run benefits and costs of various treatments.

If outcomes for study samples are measured at multiple points in time, and if a sufficient number of studies contain multiple, similar follow-up periods, we calculate effect sizes for an initial and longer term follow-up period. Using different points of time of measurement allows us to examine, via meta-regression, whether program effects change (i.e., decay or increase) over time.

Some Special Coding Rules for Effect Sizes. Most studies in our review have sufficient information to code exact mean-difference effect sizes. Some studies, however, report some, but not all the information required. We follow the following rules for these situations:

- **Two-tail p-values.** Some studies only report p-values for significance testing of program outcomes. When we have to rely on these results, if the study reports a one-tail p-value, we convert it to a two-tail test.
- **Declaration of significance by category.** Some studies report results of statistical significance tests in terms of categories of p-values. Examples include: $p<=0.01$, $p<=0.05$, or non-significant at the $p=0.05$ level. We calculate effect sizes for these categories by using the highest p-value in the category. Thus, if a study reports significance at $p<=0.05$, we calculate the effect size at $p=0.05$. This is the most cautious strategy. If the study simply states a result is non-significant, we compute the effect size assuming a p-value of 0.50.

[6] Lipsey & Wilson (2001).
[7] Ibid.
[8] Sánchez-Meca, J., Marín-Martínez, F., & Chacón-Moscoso S. (2003). Effect-size indices for dichotomized outcomes in meta-analysis. *Psychological Methods*, *8*(4), 448-467.

2.2 Procedures for Calculating Effect Sizes

Effect sizes summarize the degree to which a program or policy affects an outcome. In experimental settings this involves comparing the outcomes of treated participants relative to untreated participants. Analysts use several methods to calculate effect sizes, as described in Lipsey and Wilson.[9] The most common effect size statistic is the standardized mean difference effect size, and that is the measure we employ in meta-analysis.

Continuously Measured Outcomes. The mean difference effect size is designed to accommodate continuous outcome data, such as student test scores, where the differences are in the means of the outcome.[10] The standardized mean difference effect size is computed with:

$$(2.2)\quad ES = \frac{M_t - M_c}{\sqrt{\dfrac{(N_t - 1)SD_t^2 + (N_c - 1)SD_c^2}{N_t + N_c - 2}}}$$

In this formula, ES is the estimated effect size for a particular program; M_t is the mean value of an outcome for the treatment or experimental group; M_c is the mean value of an outcome for the control group; SD_t is the standard deviation of the treatment group; and SD_c is the standard deviation of the control group; N_t is the number of subjects in the treatment group; and N_c is the number of subjects in the control group.

We compute the variance of the mean difference effect size statistic in equation 2.2 with:[11]

$$(2.3)\quad ESVar = \frac{N_t + N_c}{N_t N_c} + \frac{ES^2}{2(N_t + N_c)}$$

In some random assignment studies or studies where treatment and comparison groups are well-matched, authors provide only statistical results from a t-test. In those cases, we calculate the mean difference effect size using:[12]

$$(2.4)\quad ES = t\sqrt{\frac{N_t + N_c}{N_t N_c}}$$

In many research studies, the numerator in equation 2.2, $M_t - M_c$, is obtained from a coefficient in a regression equation, not from experimental studies of separate treatment and control groups. For such studies, the denominator in equation 2.2 is the standard deviation for the entire sample. In these types of regression studies, unless information is present that allows the number of subjects in the treatment condition to be separated from the total number in a regression analysis, the total N from the regression is used for the sum of N_t and N_c, and the product term $N_t N_c$ is set to equal $(N/2)^2$.

Dichotomously Measured Outcomes. Many studies record outcomes not as continuous measures such as test scores, but as dichotomies; for example, high school graduation. For these yes/no outcomes, Sanchez-Meca, et al.[13] shows that the Cox transformation produces the most unbiased approximation of the standardized mean effect size. Therefore, to approximate the standardized mean difference effect size for continuously measured outcomes, we calculate the effect size for dichotomously measured outcomes with:

$$(2.5)\quad ES_{Cox} = \frac{\ln\left[\dfrac{P_t(1 - P_c)}{P_c(1 - P_t)}\right]}{1.65}$$

where P_t is the percentage of the treatment group with the outcome and P_c is the percentage of the comparison group with the outcome. The numerator, the logged odds ratio, is then divided by 1.65.

[9] Lipsey & Wilson (2001).
[10] Ibid, Table B10, equation 1, p. 198.
[11] Ibid, Table 3.2, p. 72.
[12] Ibid, Table B10, equation 2, p. 198.
[13] Sanchez-Meca et al. (2003).

The ES_{Cox} has a variance of

$$(2.6)\ \ ESVar_{Cox} = .367\left[\frac{1}{O_{1t}} + \frac{1}{O_{2t}} + \frac{1}{O_{1c}} + \frac{1}{O_{2c}}\right]$$

where O_{1t}, O_{2t}, O_{1C}, *and* O_{2C} are the number of successes (1) and failures (2) in the treatment, t, and control, c groups.

Occasionally when outcomes are dichotomous, authors report the results of statistical analysis such as chi-square (χ^2) statistics. In these cases, we first estimate the absolute value of $ES_{arcsine}$ per Lipsey and Wilson,[14] then based on analysis we conduct, we multiply the result by 1.35 to determine ES_{Cox}.

$$(2.7)\ \ |ESCox| = 1.35 * 2\sqrt{\frac{X^2}{N_t + Nc - X^2}}$$

Similarly, we determine that in these cases, using equation 2.3 to calculate the variance underestimates $ESVar_{Cox}$ and, hence over estimates the inverse variance weight. We conduct analysis which shows that $ESVar_{Cox}$ is linearly related to $ESVar$. Our analysis indicates that by multiplying $ESVar$ by 1.65 provides a very good approximation of $ESVar_{Cox}$.

Pre/Post Measures. Where authors report pre- and post-treatment measures without other statistical adjustments, first we calculate two between-groups effect sizes: (1) at pre-treatment and, (2) at post-treatment. Finally, we calculate the overall effect size by subtracting the post-treatment effect size from the pre-treatment effect size.

Effect Sizes Measured as Elasticities. Some of the research literatures we review are econometric in nature; that is, they use regression techniques econometricians often use to consider unobserved variables bias or simultaneity. The metric used in almost all of these economic studies to summarize results is an elasticity—how a percentage change in one continuously measured "treatment" affects the percentage change in a continuously measured outcome. This is a standard metric in studies conducted by economists. For example, the research literatures that measure the impact of increased incarceration rates on crime and the effects of the number of police officers on crime both use elasticities to describe the relationships. For studies that do not estimate elasticities directly, we compute the elasticity from the author's preferred regression coefficient taken at the study's mean values for crime and prison or police. Thus, the effect size for these analyses is an elasticity, rather than the other effect size metrics (Cohen's D or D-cox effect sizes) used when we conduct meta-analyses of programs. Apart from the effect size metric, all of the other meta-analytic computations follow the procedures as described in this chapter.

Adjusting Effect Sizes for Small Sample Sizes

Since some studies have very small sample sizes, we follow the recommendation of many meta-analysts and adjust for this. Small sample sizes have been shown to upwardly bias effect sizes, especially when samples are less than 20. Following Hedges,[15] Lipsey and Wilson[16] report the "Hedges correction factor," which we use to adjust all mean-difference effect sizes, (where N is the total sample size of the combined treatment and comparison groups):

$$(2.8)\ \ ES'_m = \left[1 - \frac{3}{4N-9}\right] * \ \ ES_m$$

Adjusting Effect Sizes and Variances for Multi-Level Data Structures. Most studies in the education field use data that are hierarchical in nature. That is, students are clustered in classrooms, classrooms are clustered within schools, schools are clustered within districts, and districts are clustered within states. Analyses that do not account for clustering will underestimate the variance in outcomes at the student level (the denominator in equation 2.2) and, thus, may over-estimate effect sizes. In studies that do not account for clustering, effect sizes and their variance require additional adjustments.[17]

There are two types of studies, each requiring a different set of adjustments.[18]

[14] Lipsey and Wilson, 2001, Table B10, equation 23, p. 200.
[15] Hedges, L. V. (1981). Distribution theory for Glass's estimator of effect size and related estimators. *Journal of Educational Statistics, 6*(2), 107-128.
[16] Lipsey & Wilson, 2001, equation 3.22, p. 49.
[17] Studies that employ hierarchical linear modeling, or fixed effects with robust standard errors, or random effects models account for variance and need no further adjustment.
[18] These formulas are taken from: L. Hedges. (2007). Effect sizes in cluster-randomized designs. *Journal of Educational and Behavioral Statistics, 32*(4): 341-370.

First, for student-level studies that ignore the variance due to clustering, we make adjustments to the mean effect size and its variance,

$$(2.9)\quad ES_T = ES_m * \sqrt{1 - \frac{2(n-1)\rho}{N-2}}$$

$$(2.10)\quad V\{ES_T\} = \left(\frac{N_t + N_c}{N_t N_c}\right)[1 + (n-1)\rho] + {ES_T}^2 \left(\frac{(N-2)(1-\rho)^2 + n(N-2n)\rho^2 + 2(N-2n)\rho(1-\rho)}{2(N-2)[(N-2) - 2(n-1)\rho]}\right)$$

where ρ is the intraclass correlation coefficient, the ratio of the variance between clusters to the total variance; N is the total number of individuals in the treatment group, N_t, and the comparison group, Nc; and n is the average number of persons in a cluster, K.

In the educational field, clusters can be classes, schools, or districts. For this study, we use 2006 Washington Assessment of Student Learning (WASL) data to calculate values of ρ for the school-level ($\rho = 0.114$) and the district level ($\rho = 0.052$). Class-level data are not available for the WASL, so we use a value of $\rho = 0.200$ for class-level studies.

Second, for studies that report means and standard deviations at a cluster level, we make adjustments to the mean effect size and its variance:

$$(2.11)\quad ES_T = ES_m * \sqrt{\frac{1 + (n-1)\rho}{n\rho}} * \sqrt{\rho}$$

$$(2.12)\quad v\{ES_T\} = \left\{\left(\frac{N_t - N_c}{N_t N_c}\right) * \left(\frac{1 + (n-1)\rho}{n\rho}\right) + \frac{[1 + (n-1)\rho]^2 * {ES_T}^2}{2n\rho(K-2)}\right\} * \rho$$

We do not adjust effect sizes in studies reporting dichotomous outcomes. This is because the Cox transformation assumes the entire normal di**s**tribution at the student level.[19] However, when outcomes are dichotomous, or an effect size is calculated from studies where authors control for clustering with robust standard errors or hierarchical linear modeling, we use the "design effect" to calculate the "effective sample size."[20] The design effect is given by:

$$(2.13)\quad D = 1 + (n-1)\rho$$

And the effective sample size is the actual sample size divided by the design effect. For example the effective sample size for the treatment group is:

$$(2.14)\quad N_{t(eff)} = \frac{N_t}{D}$$

In some studies, for example in a mental health setting where the treatment group receives an intervention (therapy) and the comparison group does not, the treatment group may be clustered within therapists while the comparison group is not clustered. To our knowledge, there are no published methods for corrected effect sizes and variance for such studies. Dr. Larry Hedges provided the following approach for these corrections.

We first calculate an intermediate estimate of ES.[21]

$$(2.15)\quad ES_{int} = ES * \sqrt{1 - \frac{m_t(n_t - 2)\rho}{N-2}}$$

where m_t is the number of clusters in the treatment group, and n_t is the number of subjects in the treatment group, and N is the total sample size.

Then an approximately unbiased estimate of ES_T is obtained by multiplying $\mathrm{ES}_{\mathrm{int}}$ by $J(h)$, where h is the effective degrees of freedom:[22]

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[19] Mark Lipsey (personal communication, November 11, 2007).
[20] Formulas for design effect and effective sample size were obtained from the Cochrane Reviewers Handbook, section 16.3.4. Approximate analyses of cluster-randomized trials for a meta-analysis: effective sample sizes. http://www.cochrane-handbook.org/
[21] Larry Hedges (personal communication, June 11, 2012).
[22] Ibid.

$$(2.16)\quad h = \frac{[(N-2)(\rho-1) + (n_t m_t - n_t)\rho]^2}{(N-2)(1-\rho)^2 + (n_t m_t - n_t)n_t\rho^2 + 2(n_t m_t - n_t)\rho(1-\rho)}$$

and $J(h)$ is given by:[23]

$$(2.17)\quad J(h) = 1 - \frac{3}{4h-1}$$

Thus, the final unbiased estimate of ES_T is:[24]

$$(2.18)\quad ES_T = ES_{int} * J(h)$$

The variance of the effect size when only one group is clustered is given by:[25]

$$(2.19)\quad ESVar = \frac{1+(n-1)\rho}{n_t m_t} + \frac{1-\rho}{m_c} + \frac{([N-2)(1-\rho)^2 + (n_t m_t - n_t)n\rho^2 + 2(n_t m_t - n)\rho(1-\rho] * ES_t}{2[(N-2)(1-\rho) + (n_t m_t - n_t)\rho]^2}$$

Computing Weighted Average Effect Sizes, Confidence Intervals, and Homogeneity Tests. Once effect sizes are calculated for each program effect, and any necessary adjustments for clustering are made, the individual measures are summed to produce a weighted average effect size for a program area. We calculate the inverse variance weight for each program effect and these weights are used to compute the average. These calculations involve three steps. First, the standard error, SE_T of each mean effect size is computed with:[26]

$$(2.20)\quad SE_T = \sqrt{\frac{N_t + N_c}{N_t N_c} + \frac{ES^2}{2(N_t + N_c)}}$$

Next, the inverse variance weight w is computed for each mean effect size with:[27]

$$(2.21)\quad w = \frac{1}{SE_T^2}$$

The weighted mean effect size for a group with i studies is computed with:[28]

$$(2.22)\quad \overline{ES} = \frac{\sum\left(w_i ES_{T_i}\right)}{\sum w_i}$$

Confidence intervals around this mean are then computed by first calculating the standard error of the mean with:[29]

$$(2.23)\quad SE_{\overline{ES}} = \sqrt{\frac{1}{\sum w_i}}$$

Next, the lower, ES_L, and upper limits, ES_U, of the confidence interval are computed with:[30]

$$(2.24)\quad \overline{ES_L} = \overline{ES} - z_{(1-\alpha)}\left(SE_{\overline{ES}}\right)$$

$$(2.25)\quad \overline{ES_U} = \overline{ES} + z_{(1-\alpha)}\left(SE_{\overline{ES}}\right)$$

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23 Ibid.
24 Ibid.
25 Ibid.
26 Lipsey & Wilson (2001): equation 3.23, p. 49.
27 Ibid., equation 3.24, p. 49.
28 Lipsey & Wilson (2001): p. 114.
29 Ibid.
30 Ibid.

In equations 2.24 and 2.25, $z_{(1-\alpha)}$ is the critical value for the z-distribution (1.96 for α = .05).

The test for homogeneity, which provides a measure of the dispersion of the effect sizes around their mean, is given by:[31]

$$(2.26)\ Q_i = \left(\sum w_i\, ES_i^2\right) - \frac{\left(\sum w_i\, ES_i^2\right)}{\sum w_i}$$

The Q-test is distributed as a chi-square with k-1 degrees of freedom (where k is the number of effect sizes).

Computing Random Effects Weighted Average Effect Sizes and Confidence Intervals. Next, we use a random effects model to calculate the weighted average effect size. Random effects models allow us to account for between-study variance in addition to within-study variance.[32]

This is accomplished by first calculating the random effects variance component, v[33]

$$(2.27)\ v = \frac{Q_i - (k-1)}{\sum w_i - \left(\sum wsq_i / \sum w_i\right)}$$

where wsq_i is the square of the weight of ES_i (2.21).

This random variance factor is added to the variance of each effect size and finally all inverse variance weights are recomputed, as are the other meta-analytic test statistics. If the value of Q is less than the degrees of freedom (k-1), there is no excess variation between studies and the initial variance estimate is used.

2.3 WSIPP Adjustments to Effect Sizes

In WSIPP reports, we show the results of our meta-analyses calculated with the standard meta-analytic formulas described in Chapter 2.2, above. We list the “Adjusted Effect Size” that we use in our analysis. These adjusted effect sizes, which are derived from the unadjusted results, may be smaller, larger, or equal to the unadjusted effect sizes we report.

In this section, we describe our rationale for making these adjustments. We make four types of adjustments that are necessary to better estimate the results that we are more likely to achieve in real-world settings. We make adjustments for: (a) the methodological quality of each study we include in the meta-analyses; (b) the relevance or quality of the outcome measure that individual studies use; (c) the degree to which the researcher(s) who conducts a study are invested in the program’s design; and (d) laboratory or other unusual non-“real world” settings.

2.3a Methodological Quality

Not all research is of equal quality, and this has the potential to influence the confidence that can be placed in the results of a study. Some studies are well-designed and implemented, and the results can be viewed as accurate representations of whether or not the program worked. Other studies are not designed as well; thus, less confidence can be placed in any reported differences. Studies with less-rigorous research design cannot completely control for self-selection bias or other unobserved threats to the validity of the evaluation results. This does not mean that results from these studies are of no value; rather, less confidence can be placed in any cause-and-effect conclusions drawn from the results.

For these reasons, we assign studies to different categories based on their methodology. This categorization allows us to account for potential differences in the quality of research designs and to adjust the results accordingly (if necessary).

[31] Ibid., p. 116.
[32] Borenstein, M., Hedges, L. V., Higgins, J. P. T., & Rothstein H. R. (2010). A basic introduction to fixed-effect and random-effects models for meta-analysis. *Research Synthesis Methods, 1*(2), 97-111.
[33] Ibid., p. 134.

The following research design categories are used:

- Category 5 includes well-implemented random assignment studies in which subjects are assigned to a treatment group and a control group who do not receive the treatment/program. Studies categorized as a 5 must indicate how well the random assignment occurred by reporting values for pre-existing characteristics for the treatment and control groups.
- Category 4 includes experimental random assignment studies with implementation problems or studies that use a lottery or random assignment approach from a wait-list when programs are oversubscribed. Random assignment studies in this category, for example, could have crossovers between the treatment and control groups or differential attrition rates between the groups.
- Category 3 includes natural experiments or studies that use advanced methods as an attempt to control for unobserved variables or reverse causality. Studies categorized as a 3 include instrumental-variable approaches, regression discontinuity designs, panel data with fixed effects, difference-in-differences, or a Heckman approach to modeling self-selection.[34]
- Category 2 includes quasi-experimental research designs where the treatment and comparison groups are reasonably well matched on pre-existing differences in key variables. For this category, studies must demonstrate that few, if any, significant differences are observed in relevant pre-existing variables. Alternatively, an evaluation must employ sound multivariate statistical techniques (e.g., logistic regression, hierarchical linear modeling for nested variables, or propensity score matching) to control for pre-existing differences.
- Category 1 includes quasi-experimental studies that are less well-implemented or do not use many statistical controls.

Studies that do not fit into the categories are assigned a 0 and are not included in our meta-analysis because we cannot confidently estimate a causal treatment effect of the program. These include studies where pre-existing differences between the groups were not adequately controlled or studies had no comparison group (e.g., pre/post designs that measure outcomes only for program participants before and after the program).

[34] For a discussion of these methods, see Rhodes, W., Pelissier, B., Gaes, G., Saylor, W., Camp, S., & Wallace, S. (2001). Alternative solutions to the problem of selection bias in an analysis of federal residential drug treatment programs. *Evaluation Review, 25*(3), 331-369. Schlotter, M., Schwerdt, G., & Woessman, L. (2011). Econometric methods for causal evaluation of education policies and practices: a non-technical guide. *Education Economics, 19(2),* 109-137.

2.3b Adjusting Effect Sizes for Researcher Involvement in the Program's Design and Implementation and for Laboratory or Unusual Settings

The purpose of the WSIPP's work is to identify programs that can make cost-beneficial improvements to Washington's actual service delivery system. There is some evidence that programs closely controlled by researchers or program developers have better results than those that operate in "real world" administrative structures.[35] In our evaluation of a real-world implementation of a research-based juvenile justice program in Washington, we found that the actual results are considerably lower than the results obtained when the intervention is conducted by the originators of the program.[36] Therefore, we make an adjustment to effect sizes, ES_m, to reflect this distinction. When possible, we use meta-regression to inform the magnitude of this adjustment; lacking evidence to compute an adjustment empirically, we make an adjustment based on *a priori* assumptions.

2.3c Adjusting Effect Sizes for Evaluations with Weak Outcome Measures

Some evaluations use outcome measures that may not be precise gauges of the ultimate outcome of interest. In these cases, we record a flag that we can use later to discount the effect. For example, in program evaluations that measure child mental health outcomes, such as ADHD, the "gold standard" measure would be an official diagnosis of ADHD. However, some studies may report psychiatrist ratings of symptom severity rather than a standardized diagnosis measure. The psychiatrist ratings are no doubt meaningful, but an analyst may flag such ratings as weaker outcome measures.

2.3d Values of Adjustment Factors

An explicit adjustment factor (multiplier) is assigned to the results of individual effect sizes based on WSIPP's judgment concerning research quality (study design), research involvement in program design and implementation, "laboratory" setting, and weak outcome measure. Adjustments are made by multiplying the effect size for any study, $ES'm$ in equation 2.8 by the adjustment factors for the topic area. The resulted adjusted effect size is used in the benefit-cost analysis.

For research areas with a limited number of studies, we use the *a priori* multipliers listed in Exhibit 1. The *a priori* multipliers are subjective; they are based on WSIPP's general impressions of the confidence that can be placed in the predictive power of evaluations of different quality, weak outcome measures, program developer involvement in evaluation, and unusual settings.

When we have a sufficient number of studies in a research area (e.g., crime, child welfare, K–12 education), we determine adjustment factors based on results of meta-regression techniques (multivariate linear regression analysis, weighting with random effects inverse variance weights). In some topic areas, the adjustment factors generated by the regression analysis are similar to the *a priori* values. However, in several topic areas (e.g., crime and early childhood education), we found no effect of study design on effect size. The detailed benefit-cost results accessible from the WSIPP website (http://www.wsipp.wa.gov) describe the multipliers used for each program.

The effect of the adjustment factors frequently produces a smaller adjusted effect size. For example, using the *a priori* adjustments, if a study with $ES'm$ of -0.20 is deemed a level 4 study, then the -0.20 effect size would be multiplied by 0.75 to produce a -0.15 adjusted effect size for use in the benefit-cost analysis.

[35] Lipsey, M. W. (2003). Those confounded moderators in meta-analysis: Good, bad, and ugly. *The Annals of the American Academy of Political and Social Science, 587*(1), 69-81. Lipsey found that, for juvenile delinquency evaluations, programs in routine practice (i.e., "real world" programs) produced effect sizes only 61% as large as research/demonstration projects. See also: Petrosino, A. & Soydan, H. (2005). The impact of program developers as evaluators on criminal recidivism: Results from meta-analyses of experimental and quasi-experimental research. *Journal of Experimental Criminology, 1*(4), 435-450.

[36] Barnoski, R. (2004). *Outcome evaluation of Washington State's research-based programs for juvenile offenders.* (Document No. 04-01-1201). Olympia: Washington State Institute for Public Policy.

Exhibit 1
***A Priori* Adjustment Factors Applied to the Meta-Analysis**

Type of Multiplier	Adjustment factor
Study Design	
1—Less well-implemented comparison group or observational study, with some covariates	0.5
2—Well-implemented comparison group design, often with many statistical controls	0.5
3—Well-done observational study with many statistical controls (e.g., IV, regression discontinuity)	0.75
4—Random assignment, with some RA implementation issues	0.75
5—Well-done random assignment study	1.00
Program developer = researcher	0.5
Unusual (not real world) setting	0.5
Weak measurement used	0.5

Chapter 3: Procedures to Compute "Monetizable" Outcome Units

Chapter 2 described the procedures WSIPP uses to compute effect sizes and standard errors. Chapter 3 describes our procedures to convert effect sizes into units of outcomes that can be monetized. Chapter 4 then describes how monetary values are attached to these "monetizable" units of outcomes.

To estimate the expected change in the number of monetizable units resulting from a program or policy, WSIPP's approach draws on two bodies of research: (1) effect sizes from program evaluation research that measure how a program influences an outcome, and (2) effect sizes from other research that estimate the causal linkage between two different outcomes. The goal is to combine the best current information from these two bodies of research to derive benefit-cost estimates for program and policy choices.

- **Direct Program Effect Sizes for Specific Measured Outcomes.** The first type of effect size measures the estimated direct effect of a program or policy on a particular outcome. We take these direct effect sizes from the original research study itself or, more typically, from a meta-analysis of a set of program evaluations on a particular topic. An example of the first type of effect size is an evaluation or meta-analysis that directly measures a credible causal relationship between a program such as Nurse Family Partnership and the rate of substantiated child abuse and neglect. In the procedures described below, direct program effect sizes are denoted as PES_o and represent the estimated program effect size on some measured outcome o. The standard error of this effect size, also computed from the original program evaluation or meta-analysis, is denoted as $PESSE_o$. Some of these program effect sizes can be monetized directly. To continue the example, a change in substantiated child and abuse can be expected to cause changes in child welfare system costs and in the victimization costs to the child (as we describe in Chapter 4).
- **Linked Effect Sizes on "Monetizable" Outcomes.** The second type of effect size we use in the benefit-cost model takes advantage of a different body of research that measures how one particular outcome is causally related to another outcome to which a monetary value can be estimated. An example of the second type of effect size is a (separately estimated) causal linkage between child abuse and neglect and the probability of graduating from high school. Graduating from high school, as we describe in Chapter 4, is an outcome for which monetary benefits can be attached. Thus, while the program itself may only directly measure an outcome such as child abuse and neglect, the separately estimated linked relationship between child abuse and neglect and high school graduation can be used, in conjunction with the primary research finding, to estimate monetary benefits of the program's *indirect* effect on high school graduation. The word "indirect" here just means that while the original program evaluation may not measure a relevant outcome directly; there may be a separate body of credible research indicating a causal relationship between a directly measured outcome and another outcome that can be monetized. In the models below, the "linked" effect sizes are denoted as LES_{om} and represent the estimated effect size between a measured outcome o and a monetizable outcome m. The standard error for this linkage, which is computed from the body of research, is denoted as $LESSE_{om}$.

The procedures outlined below describe how these two types of effect sizes are combined to produce estimates of the units to which monetary values are attached. The product of the procedures is a variable, $Units_m$ that measures the mean number of units of an outcome, *m* that can be monetized with WSIPP's benefit-cost model. For example, the units of high school graduation, $Units_{hsgrad,}$ might be +0.03, which would indicate three extra percentage points on a high school graduation rate.

3.1 Input Screen for Program Effect Size Parameters

The procedures described below use a number of user-supplied parameters.

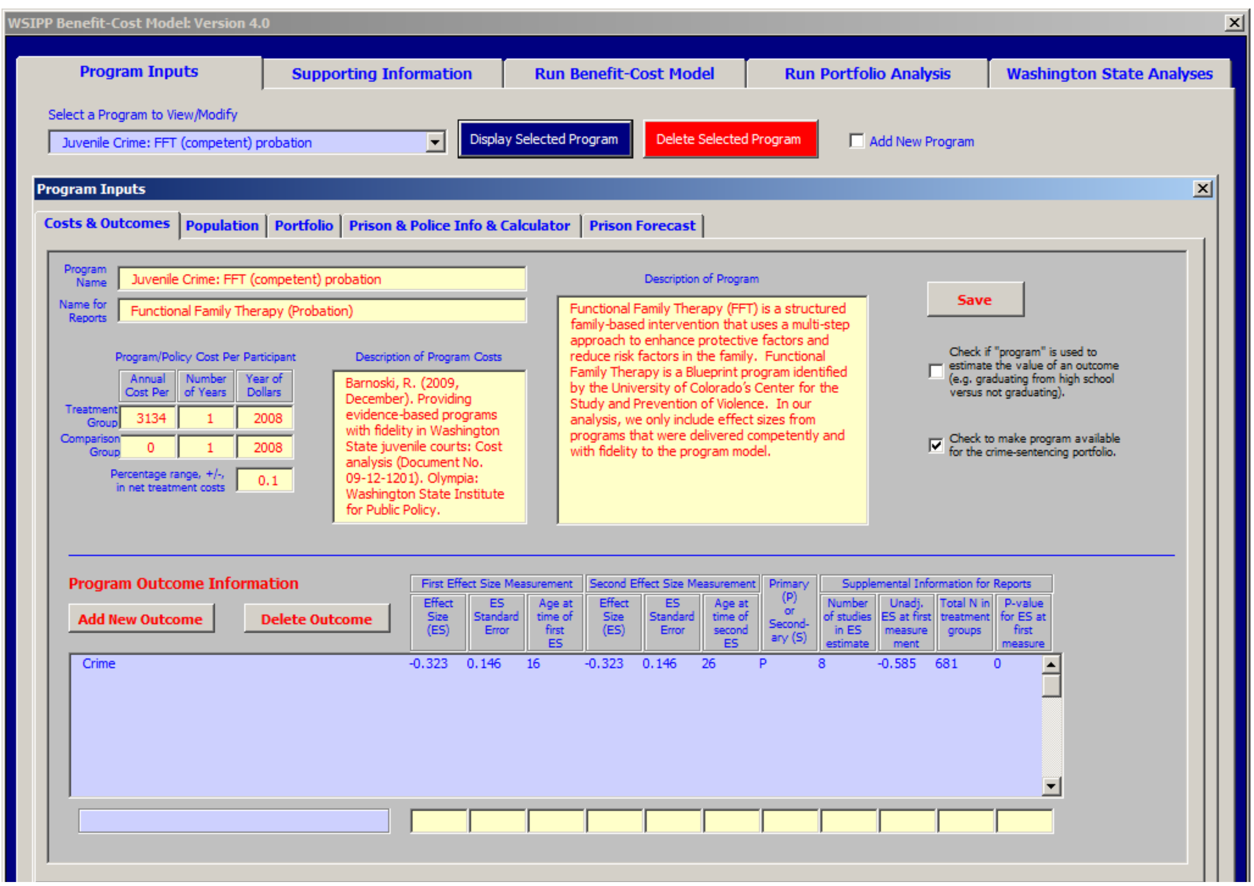
Some program evaluations measure outcomes just once. For example, a person might be a participant in a program at a certain age and an evaluation measures an outcome at a second age. Some evaluations then measure the same outcome at a subsequent age. Information on how effect sizes change over time can be useful when estimating benefits. WSIPP's benefit-cost model is structured to model an outcome measured at two different post-treatment time intervals. This provides the capability to model program effects that decay, or grow, over time.

The estimated effect of a policy or program on an outcome over time, and the standard error in this estimate, is operationalized in WSIPP's benefit-cost model with eight parameters for each program or policy.

Mage1	average age of a person when an effect size of the program is first measured
PES1	estimated effect size of a program at *Mage1*
PESSE1	estimated standard error of the effect size of a program at *Mage1*
Mage2	average age of a person when an effect size of the program is measured or estimated a second time
PES2	estimated effect size of a program at *Mage2*
PESSE2	estimated standard error of the effect size of a program at *Mage2*
Tage	average age of a person treated with a program
BaseRate	estimated outcome for the non-treatment group (e.g., the predicted outcome in absence of the program). For dichotomous outcomes, this is a percentage, for continuous outcomes, it is the standard deviation of the outcome being measured. The *BaseRate* may change with the age of the participant; it is not necessarily a single number.

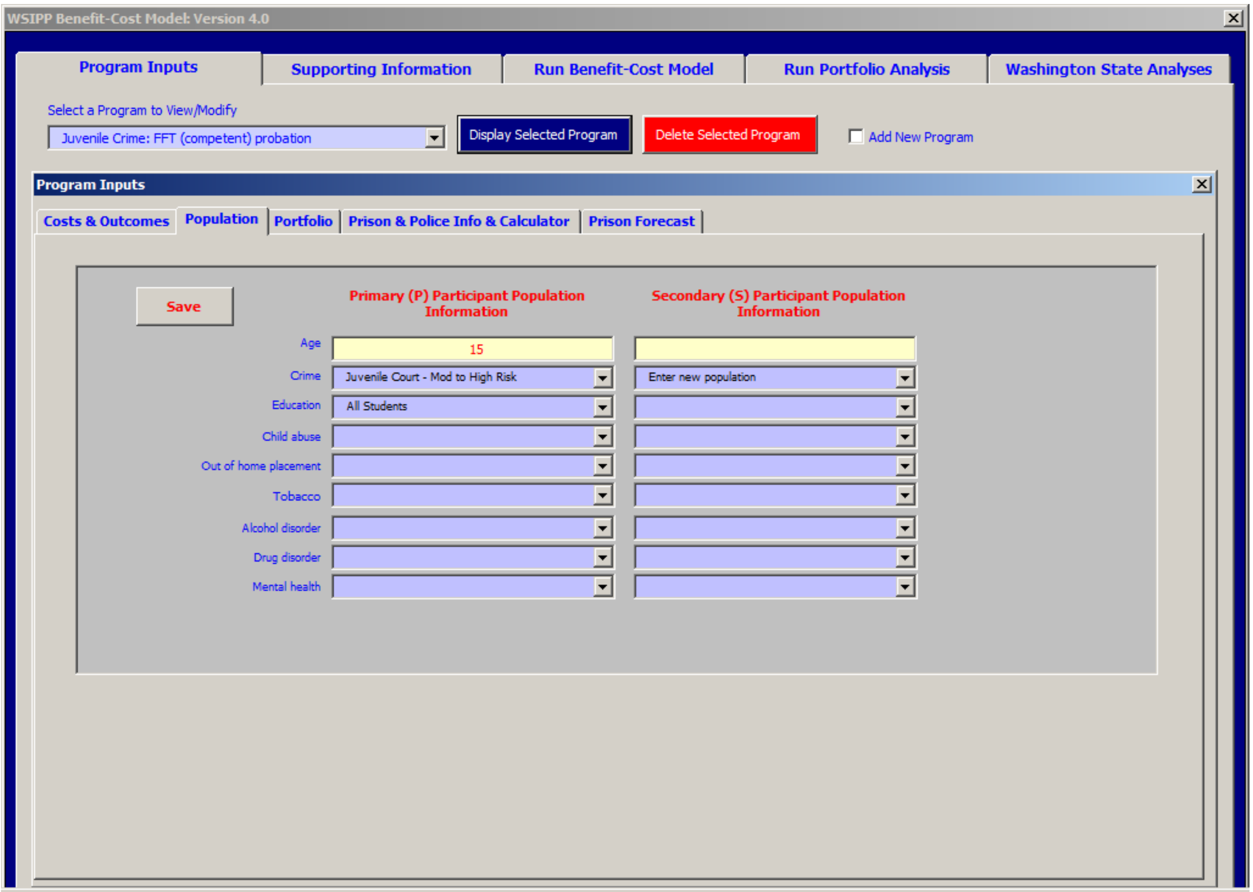
Exhibit 2 displays a screen shot of the benefit-cost model displaying where most of these eight parameters are entered for each program, for each outcome. The example shown is the juvenile justice program Functional Family Therapy (FFT). The assumed treatment age for a juvenile in this program is 15. In the program outcome section of the screen, the user entered six of the eight parameters for the crime outcome measured for FFT. The first effect size is -0.323 and is measured at age 16 and has a standard error of 0.146. For this program, our review of the FFT evaluations indicates that the average follow-up period is about one year; thus, we enter age 16 as *Mage1*. The second effect size, -0.323, is entered for age 26 with a standard error of 0.146. WSIPP's practice for all programs, such as FFT, that measure an effect size at one follow-up period is to use that adjusted effect size and the standard error for both *Mage1* and *Mage2*. We also set the *Mage2* age ten years beyond the first measured effect size.

Exhibit 2



The seventh and eighth parameters, *Tage* and *BaseRate*, are entered on a second input screen, as shown in Exhibit 3. *BaseRate* is applied after the user selects the appropriate population from the drop-down menus in the screen. The actual base rates are entered on other input screens in the software application.

Exhibit 3



3.2 Unit Changes from Direct Effect Sizes

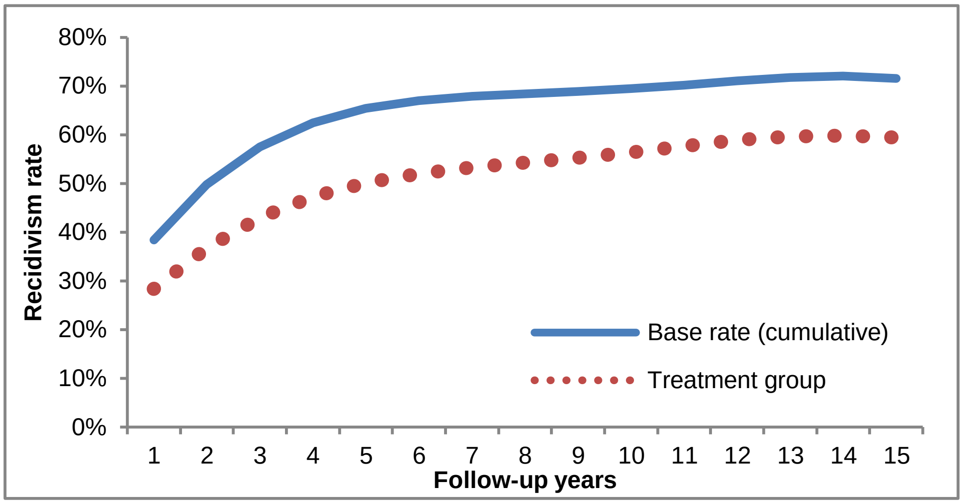
Once these eight parameters are exogenously computed and entered into the model, we follow these steps to compute monetizable units. First, we compute unit changes for outcomes directly measured by the program evaluations.

For dichotomous outcomes:

1. At $Mage1$ and $Mage2$, using the D-cox effect size formula (see Chapter 2), we apply $PES1$ and $PES2$ to the base rates at those two ages to compute the change in monetizable units ($Units_m$) at $Mage1$ and $Mage2$.
2. We then calculate the relative risk ($Units_m$ / $BaseRate$) at $Mage1$ and $Mage2$.
3. For ages ranging from $Tage$ to $Mage1$, we apply the relative risk calculated at $Mage1$ to the base rates between $Tage$ and $Mage1$ to compute the $Units$ between $Tage$ and $Mage1$.
4. For ages beyond $Mage2$, we apply the relative risk calculated at $Mage2$ to the base rates after $Mage2$ to compute the $Units_m$ for all years after $Mage2$.
5. For ages ranging from $Mage1$ to $Mage2$, we linearly interpolate the relative risk at each age, and apply that value to the base rates for those ages, to compute the $Units_m$ between $Mage1$ and $Mage2$.

The results of this analysis can be best displayed with an example. Exhibit 4 below shows the amount of change we monetize from the FFT example above. That amount of change we would expect to result from the program is the space between the base rate and the treatment group rate in the chart below.

Exhibit 4



For continuous outcomes:

> The unit change ($Units_m$) at each age is simply the effect size (standardized mean difference, see Chapter 2) multiplied by the standard deviation unit in which the outcome is measured.

As discussed above, some effect sizes are expressed in the form of elasticities. Currently, for crime-related prison and police elasticities we use a different set of procedures to compute units of change. See Chapter 4.2f for details.

3.3 Unit Changes from Linked Effect Sizes

For linked effect sizes, we allow the user to enter a single effect size, standard error, and age of measurement. The unit changes for linked effect sizes are computed as described in the previous section. However, since there is no *Mage2,* for dichotomous outcomes, we compute the relative risk (*Unitsm* / base rate), using the D-cox effect size formula, at *Mage1*. We then apply that relative risk to the base rates at all ages (*Tage* and beyond). For continuous outcomes, the unit change at each age is simply the effect size at *Mage1,* multiplied by the standard deviation unit in which the outcome is measured.

3.4 Monetizable Units for Benefit-Cost Calculation

The units of change for effect sizes monetized in the benefit-cost model are simply the multiplicative product of the directly measured (program) and indirect (linked) effect sizes. That is, for a program outcome such as academic test scores, for which do not assume a linkage to other outcomes, the units of change for a program effect size will be the units of change in test scores multiplied by one. For an outcome such as juvenile crime, for which we estimate a linkage to high school graduation, we calculate two sets of unit changes. For the direct (crime) measure, we simply use the unit change for crime multiplied by one. For the indirect (high school graduation) measure, we multiply that unit change in crime by the unit change for the link between crime and high school graduation.

Chapter 4: Methods Used to Estimate Monetary Benefits of Outcome Units

As summarized in Chapter 1, the WSIPP model is an integrated set of estimates and computational routines designed to produce internally consistent benefit-to-cost estimates for a variety of public policies and programs. The model implements a standard economic calculation of the expected worth of an investment by computing the net present value of a stream of estimated benefits and costs that occur over time, as described with equation 4.1.

$$(4.1) \quad NPV_{tage} = \sum_{y=tage}^{N} \frac{Q_y \times P_y - C_y}{(1+Dis)^y}$$

In this basic model, the net present value (NPV) of a program is the quantity of the outcomes produced by the program or policy (Q) in year y, times the price per unit of the outcome (P) in year y, minus the cost of producing the outcome (C) in year y. The lifecycle of each of these values is present-valued to the average age a person is treated ($tage$) and covers the number of years into the future over which they are evaluated (N). The future values are expressed in present value terms after applying a discount rate (Dis). An internal rate of return on investment can also be calculated from these annual cash flows. As noted, many of the values summarized in equation 4.1 are estimated or posited with uncertainty; we model this uncertainty using a Monte Carlo simulation to estimate the riskiness of benefit-cost results.

The first term in the numerator of equation 4.1, Q_y, is the estimated number of outcome "units" in year y produced by the program or policy. The procedures we use to develop estimates of Q_y are described in Chapters 2 and 3. In Chapter 4 we describe the various methods we use to estimate the price term, P_y, in equation 4.1.

4.1 Valuation of Labor Market Outcomes

Several of the outcomes measured in the benefit-cost model are monetized, in part, with labor market earnings. Measuring the earnings implications of human capital variables is a common approach in economics.[37]

In the current version of the benefit-cost model, the following outcomes are monetized, in part, with labor market earnings (see Chapter sections in parentheses for more information on each outcome):

- High school graduation (Chapter 4.7)
- Standardized student test scores (Chapter 4.7)
- Number of years of completed education (Chapter 4.7)
- Morbidity and mortality costs of alcohol and illicit drug disorders, and regular smoking (Chapter 4.4)
- Morbidity and mortality costs of mental health disorders (Chapter 4.8)

This section discusses the data sources we use for estimates of labor market earnings. Other parts of Chapter 4, as noted above, present additional parameters for the specific outcomes listed above, along with the computational routines to produce labor market earnings benefits.

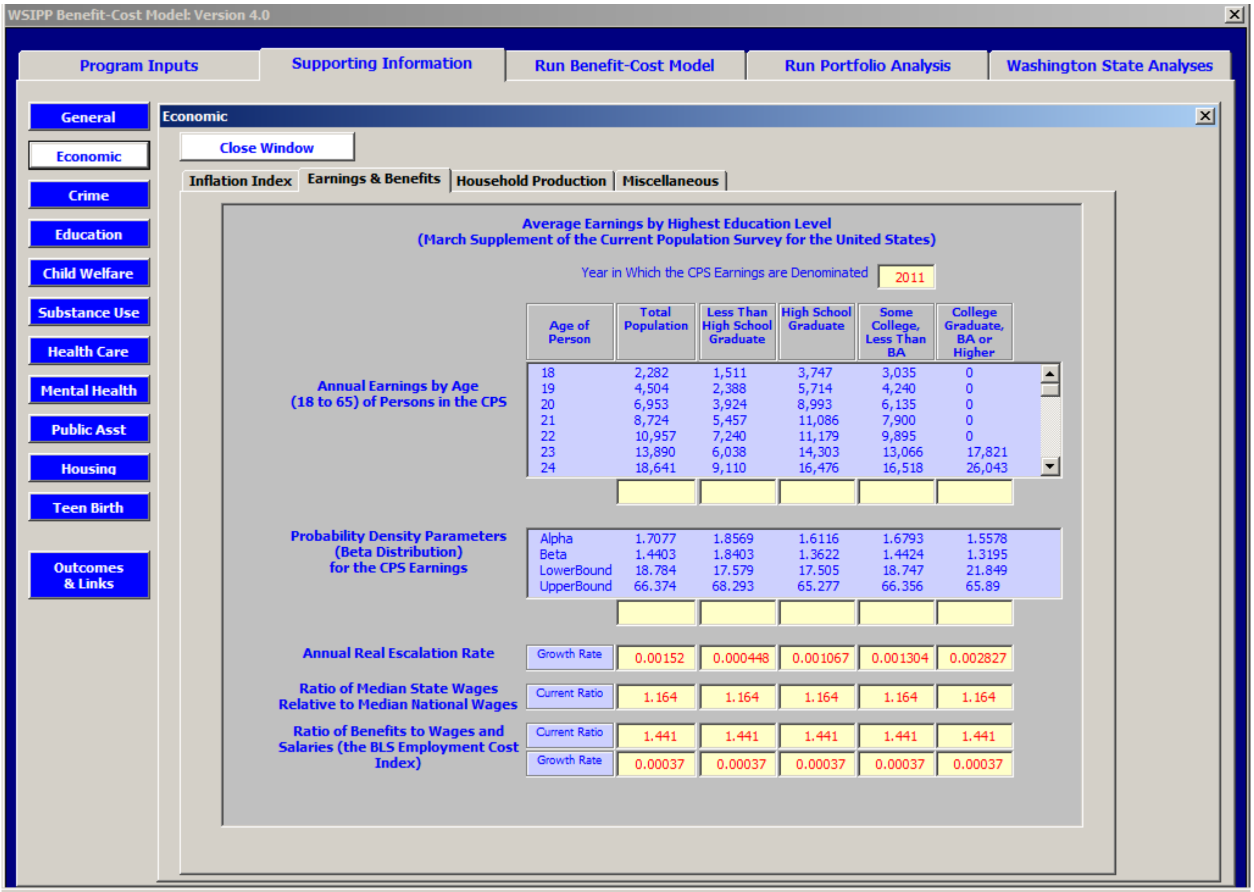
4.1a Earnings Data and Related Parameters

In this analysis, all earnings estimates derive from a common dataset. The estimates are taken from the U.S. Census Bureau's March Supplement to the Current Population Survey (CPS), which provides, annually, cross sectional data for earnings by age and by educational status.[38] These data are representative of the United States population, not just those living in Washington State. Exhibit 5 shows an input screen from the WSIPP's benefit-cost model that displays the CPS data and related parameters we use in the benefit-cost model.

[37] See, for example, Heckman et al., 2010. See also, Rouse, C. E. (2007). Consequences for the labor market. In Belfield, C. R. & Levin, H. M. (Eds.), *The price we pay: Economic and social consequences of inadequate education:* pp. 99-124. Washington, DC: Brookings Institution.; Krueger, A. B. (2003). Economic considerations and class size. *The Economic Journal, 113*(485), F34-F63; and Hanushek, E. A. (2004). *Some simple analytics of school quality* (NBER Working Paper No. 10229). Cambridge, MA: National Bureau of Economic Research.

[38] The data are accessed from the "DataFerrett" application of the U. S. Department of Commerce, Bureau of the Census, available from http://dataferrett.census.gov.

Exhibit 5



From a recent annual March supplement to the CPS, we collect average personal earnings by age of each person and by educational status. We gather the following three "person variables" from the CPS: (1) PEARNVAL, person total earnings—this variable measures income from earnings, not total money income; (2) A_AGE, age by single year; and (3) A_HGA, educational attainment by the highest level completed. From these data we compute average earnings per person, by single year of age for five educational status groupings:

- the total population—that is, the entire CPS sample (WSIPP variable name: *CPSEarnAll*);
- those who did not report completing high school but completed 7th grade or higher (*CPSEarnNHSG*);
- those who reported completing high school with a diploma (*CPSEarnHSG*);
- those with some college, but not a BA degree (*CPSEarnSomeCol*); and
- those with a BA degree or higher (*CPSEarnBA+*).

It is important to note that the average earnings reported are for all people at each age, not just for those with earnings. Thus, the data series measure both earnings of the earners and the rate of labor force participation.

From these five annual earnings streams for a recent CPS year (for example, the 2012 CPS report contains data for 2011 earnings), we fit probability density distributions. We use Palisade Corporation's *@Risk* program to select the probability distribution with the lowest root mean square error. For all five series, we found the best probability distribution to be a beta distribution. The four fitted beta distribution parameters (*ALPHA*, *BETA*, *LowerAge*, and *UpperAge*) for these distributions are then entered into the model, as shown in Exhibit 5. These beta distributions are used to allocate the sum of all cross-sectional total earnings reported for all ages for the particular education cohort. For example, for the annual earnings estimates for the total population in the CPS sample (*CPSEarnAll*), we compute the following for each year y:

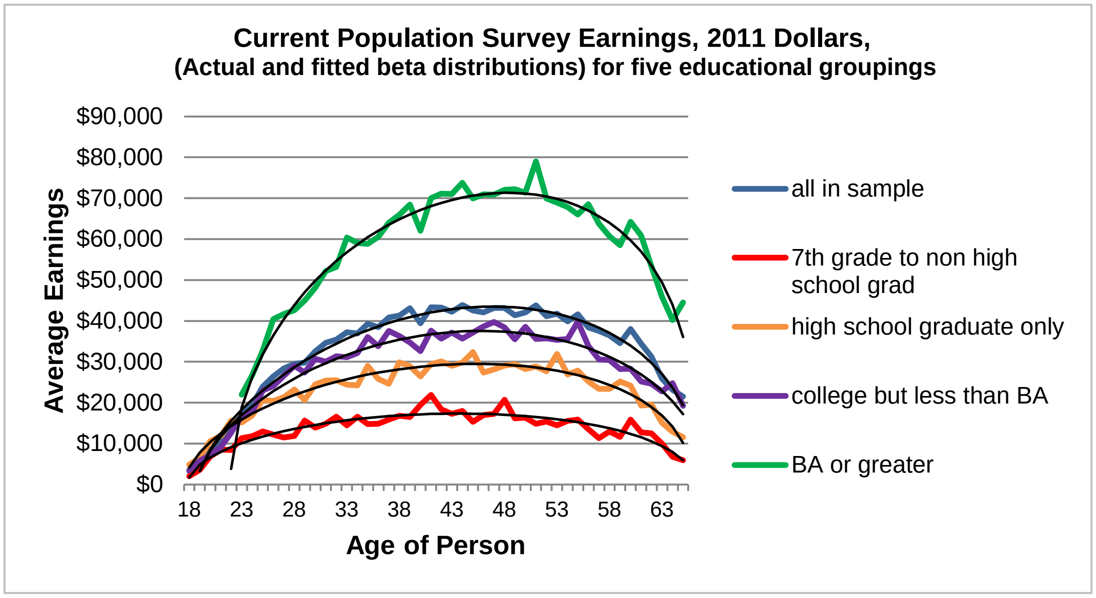
$$(4.2)\quad EarnAll_y = \left[\sum_{t=18}^{65} CPSEarnAll_t\right] \times \left[\frac{(y - LowerAge)^{ALPHA-1} \times (UpperAge - y)^{BETA-1}}{\mathrm{B}(ALPHA, BETA) \times (UpperAge - LowerAge)^{ALPHA+BETA-1}}\right]$$

Where $ALPHA$ and $BETA$ are the estimated shape parameters for the beta distribution for the total population CPS earnings, and $LowerAge$ and $UpperAge$ are the estimated continuous bounding parameters for the total population CPS earnings. B is the beta function which can be calculated in Microsoft Excel for the total population CPS earnings with:

$$(4.3)\quad B(alpha, beta) = \frac{EXP\left[GAMMALN(alpha)\right] \times EXP\left[GAMMALN(beta)\right]}{EXP\left[GAMMALN(alpha + beta)\right]}$$

We use the same process to estimate the annual CPS earnings streams for the four other educational achievement groups, substituting the relevant parameters for each group. The raw CPS earnings data, along with the fitted curves from these procedures are plotted below.

Exhibit 6



State-specific Adjustment for Wages. Although the CPS collects data on geography (i.e., what census area participants live in), the sample size for Washington State is not sufficient to calculate earnings by age for our state only. Therefore, we use an adjustment ratio to approximate earnings in Washington State relative to the national average. We use an analysis of state median household income from the Census Bureau to approximate the ratio of Washington State wage earnings to national wage earnings.[39] At this time, we are unable to compute separate ratios for the different educational groups; however, we have built in education level-specific inputs (as shown in Exhibit 5) for potential use in the future.

Growth Rates in Earnings. Since these CPS data are cross sections for the most recent CPS year, and since our benefit cost analysis reflects life-cycle earnings, we also compute an estimate of the long-run real rate of escalation in earnings for each of the five groups. We collect the same cross-sectional CPS information for the five groups for all of the years electronically available from the Census website: 1992 (with data for 1991) to 2012 (with data for 2011). We adjust each series for inflation using the United States Implicit Price Deflator for Personal Consumption Expenditures from the U.S. Department of Commerce, as published and forecasted by the Washington Economic and Revenue Forecast Council. We then fit linear-log models (earnings = a +b(ln(year))) to each of the five series. The actual data and the fitted linear-log models are shown in Exhibit 7.

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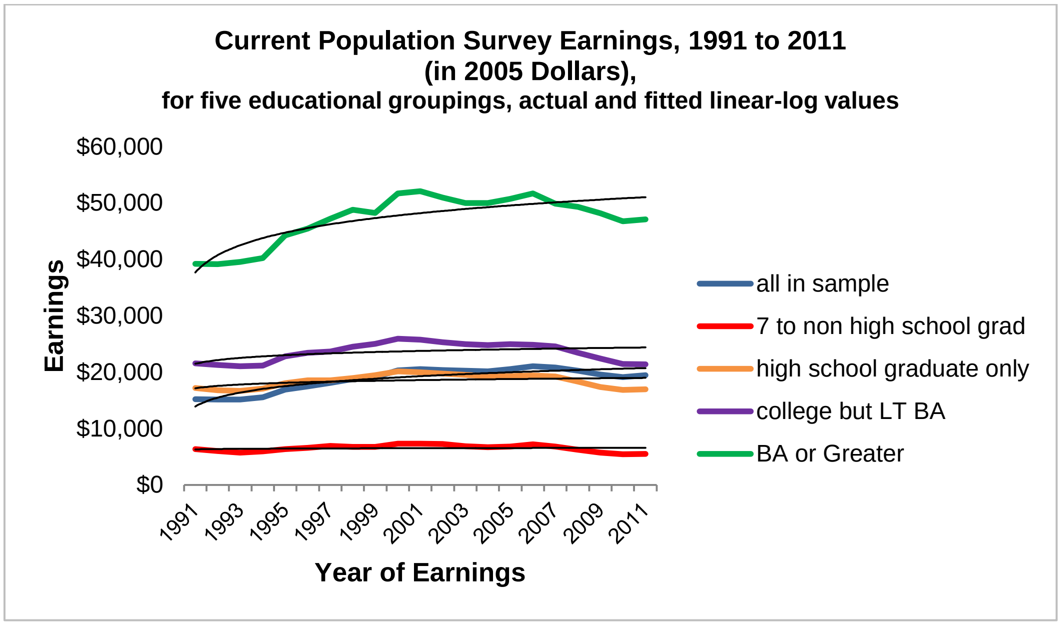
[39] We use the three-year average median income for 2009-2011 from Table H-8B. *Median Income of Households by State Using Three-Year Moving Averages: 1984 to 2011*. Retrieved August 9, 2013, from: http://www.census.gov/hhes/www/income/data/statemedian/index.html. To check the reasonableness of this proxy for individual wage earnings, we also looked at the Occupational Employment Statistics from the Bureau of Labor Statistics (http://data.bls.gov/oes/). For a single month (May 2012), the ratio computed for the annual median wage of Washington State versus national was 1.165, nearly identical to the ratio of 1.164 from the Census Bureau data.

Exhibit 7



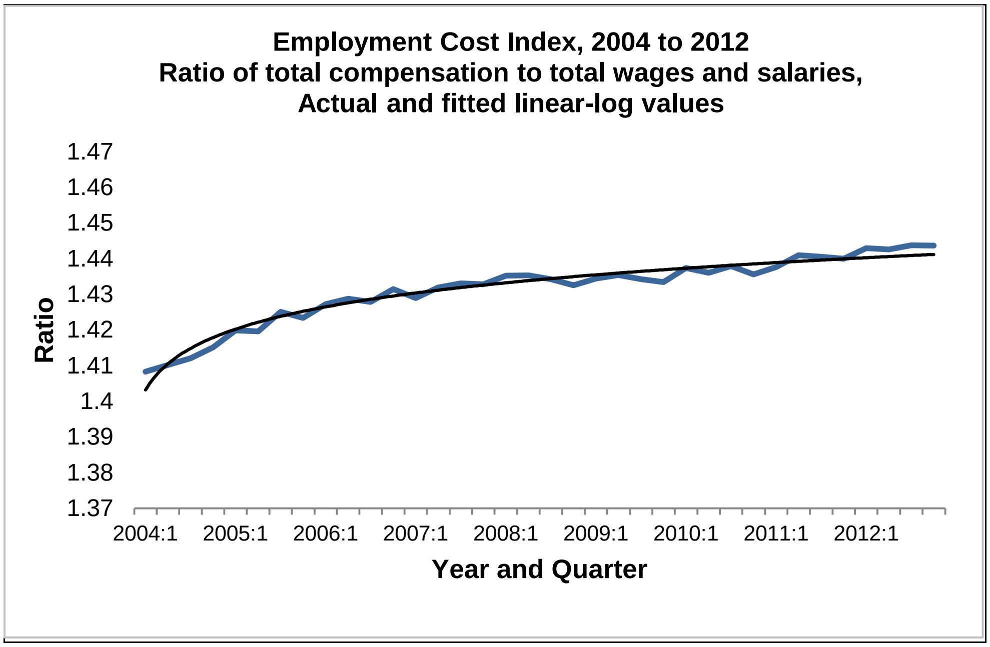
From the linear-log regression coefficients, we then estimate the real growth in wages between 1991 and 2011. We estimate the forecasted earnings at age 18 and age 48 for each of the educational groupings, then compute the average annual growth for each group. These estimates of the annual real rate of change in wages are then entered into the model, as shown in Exhibit 5.

Employee Benefits. The CPS data are for earnings and do not include employee benefits associated with earnings. To measure these additions to earnings, we include an estimate of the ratio of total employee compensation to wage and salaries. We compute these estimates from the Bureau of Labor Statistics (BLS) Employer Cost Index (ECI).[40] According to the Bureau of Labor Statistics, the benefits covered by the ECI are: "Paid leave—vacations, holidays, sick leave, and personal leave; supplemental pay—premium pay for work in addition to the regular work schedule (such as overtime, weekends, and holidays), shift differentials, and nonproduction bonuses (such as year-end, referral, and attendance bonuses); insurance benefits—life, health, short-term disability, and long-term disability; retirement and savings benefits—defined benefit and defined contribution plans; and legally required benefits—Social Security, Medicare, federal and state unemployment insurance, and workers' compensation."

The chart below displays the quarterly national ECI ratio of total compensation to total wages for all civilian workers. We fit a linear-log model (ratio = a +b(ln(quarter))) to the series and estimate the annual values for 2012 and 2042, and then compute a forecast of the annual rate growth in the benefit ratio over the 30 year interval. The current year value and the growth rate are then entered into the model, as shown in Exhibit 5. Unfortunately, the current BLS ECI does not allow the index or the growth rate to be broken out by education achievement level. Therefore, the same values are entered for each group. It is plausible that there are differences in the base rate and the expected growth rate in benefits by educational level. The model is structured so that these parameters can be included in the future.

[40] U.S. Bureau of Labor Statistics. (2013, July 17). *Employer costs for employee compensation—June 2013* (USDL-11-1140), Washington DC: Author. Data retrieved August 5, 2013 from ftp://ftp.bls.gov/pub/special.requests/ocwc/ect/ececqrtn.txt.

Exhibit 8



The earnings series is then used in the benefit-cost model to estimate labor market-related benefits of a number of outcomes. For example, in each year (y), the basic CPS earnings series is adjusted with the factors:

$$(4.4)\quad ModEarnAll_y = \left(EarnAll_y \times (1 + EscAll)^{y-tage}\right) \times \left(FAll \times (1 + EscFAll)^{y-tage}\right) \times \left(IPD_{base}/IPD_{cps}\right)$$

In this example, for each year (y) from the age of a program participant ($tage$) to age 65, the annual CPS earnings for all people ($EarnAll$) are multiplied by one plus the relevant real earnings escalation rate ($EscAll$) raised to the number of years after program participation, times the fringe benefit rate for all people ($FAll$), multiplied by one plus the relevant fringe benefit escalation rate ($EscFAll$) raised to the number of years after program participation, times a factor to apply the Implicit Price Deflator for the base year dollars (IPD_{base}) chosen for the overall benefit-cost analysis relative to the year in which the CPS data are denominated (IPD_{cps}).

4.2 Valuation of Crime Outcomes

This section describes WSIPP's benefit-cost model that estimates the monetary value to taxpayers and victims of programs that reduce crime. In this Chapter, we describe the methods, data sources, and estimation procedures.

The current version of WSIPP's model approaches the crime valuation question from two perspectives. We compute the value to taxpayers if a crime is avoided. We also estimate the costs that can be avoided by people who would otherwise have been a victim of a crime, had the crime not been averted.[41] To model avoided crime costs from these two perspectives, we estimate life-cycle costs of avoiding seven major types of crime and 11 types of costs incurred as a result of crime. In addition to computing monetary values of avoided crime, the model is also used to estimate and count the number of prison beds and victimizations avoided when crime is reduced.

The crime model uses four broad types of inputs: per-unit crime costs; sentencing probabilities and resource-use estimates; longitudinal criminological information about different populations; and estimates of multiple crimes per officially recorded crimes, such as arrests or convictions. This section begins by describing these four data sources and then turns to the computational procedures that produce the avoided costs of reduced crime.

[41] There are other costs of crime that have been posited by some commentators and analysts, including private costs and other public sector costs. WSIPP's current model does not address these additional cost categories or does so only indirectly. Future versions of this model may incorporate some of these additional cost categories.

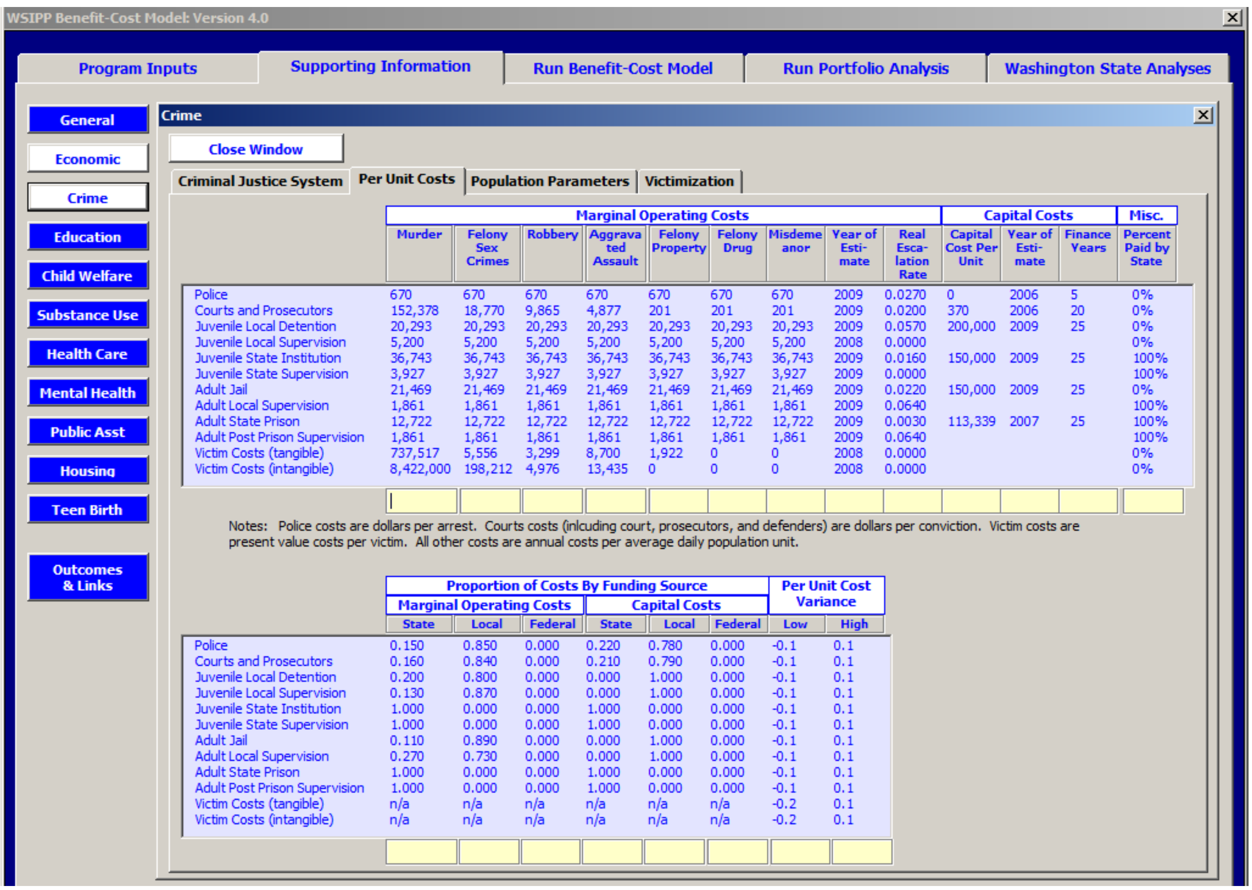
4.2a Per-Unit Crime Costs

In WSIPP's benefit-cost model, the costs of the criminal justice system paid by taxpayers are estimated for each significant part of the publicly financed system in Washington. The sectors modeled include the costs of police and sheriffs, superior courts and county prosecutors, local juvenile corrections, local adult corrections, state juvenile corrections, and state adult corrections. The estimated costs include operating costs and annualized capital costs for the capital-intensive sectors. As noted, we also include estimates of the costs of crime to victims.

For criminal justice system costs, the estimates are *marginal* operating and capital costs.[42] Marginal criminal justice costs are defined as those costs that change over a period of several years as a result of changes in a crime workload measure. Some short-run costs change instantly when a workload changes. For example, when one prisoner is added to the state adult corrections' system, certain variable food and service costs increase immediately, but new staff are not typically hired right away. Over the course of a governmental budget cycle, however, new corrections' staff are likely to be hired to reflect the change in average daily population of the prison. In WSIPP's analysis, these "longer-run" marginal costs have been estimated. The longer-run marginal costs reflect both the immediate short-run changes in expenditures, as well as those operating expenditures that change after governments make adjustments to staffing levels, often in the next few budget-writing cycles.

Exhibit 9 shows a screen shot, taken from WSIPP's benefit-cost model, that displays an array of per-unit costs for the 11 sectors and seven types of crime modeled. The estimates for each row in Exhibit 9 are described below, along with the sources of the per-unit costs and the uncertainty around the estimates.

Exhibit 9



	Marginal Operating Costs									Capital Costs			Misc.
	Murder	Felony Sex Crimes	Robbery	Aggravated Assault	Felony Property	Felony Drug	Misdemeanor	Year of Estimate	Real Escalation Rate	Capital Cost Per Unit	Year of Estimate	Finance Years	Percent Paid by State
Police	670	670	670	670	670	670	670	2009	0.0270	0	2006	5	0%
Courts and Prosecutors	152,378	18,770	9,865	4,877	201	201	201	2009	0.0200	370	2006	20	0%
Juvenile Local Detention	20,293	20,293	20,293	20,293	20,293	20,293	20,293	2009	0.0570	200,000	2009	25	0%
Juvenile Local Supervision	5,200	5,200	5,200	5,200	5,200	5,200	5,200	2008	0.0000				0%
Juvenile State Institution	36,743	36,743	36,743	36,743	36,743	36,743	36,743	2009	0.0160	150,000	2009	25	100%
Juvenile State Supervision	3,927	3,927	3,927	3,927	3,927	3,927	3,927	2009	0.0000				100%
Adult Jail	21,469	21,469	21,469	21,469	21,469	21,469	21,469	2009	0.0220	150,000	2009	25	0%
Adult Local Supervision	1,861	1,861	1,861	1,861	1,861	1,861	1,861	2009	0.0640				100%
Adult State Prison	12,722	12,722	12,722	12,722	12,722	12,722	12,722	2009	0.0030	113,339	2007	25	100%
Adult Post Prison Supervision	1,861	1,861	1,861	1,861	1,861	1,861	1,861	2009	0.0640				100%
Victim Costs (tangible)	737,517	5,556	3,299	8,700	1,922	0	0	2008	0.0000				0%
Victim Costs (intangible)	8,422,000	198,212	4,976	13,435	0	0	0	2008	0.0000				0%

Notes: Police costs are dollars per arrest. Courts costs (inlcuding court, prosecutors, and defenders) are dollars per conviction. Victim costs are present value costs per victim. All other costs are annual costs per average daily population unit.

	Proportion of Costs By Funding Source						Per Unit Cost Variance	
	Marginal Operating Costs			Capital Costs				
	State	Local	Federal	State	Local	Federal	Low	High
Police	0.150	0.850	0.000	0.220	0.780	0.000	-0.1	0.1
Courts and Prosecutors	0.160	0.840	0.000	0.210	0.790	0.000	-0.1	0.1
Juvenile Local Detention	0.200	0.800	0.000	0.000	1.000	0.000	-0.1	0.1
Juvenile Local Supervision	0.130	0.870	0.000	0.000	1.000	0.000	-0.1	0.1
Juvenile State Institution	1.000	0.000	0.000	1.000	0.000	0.000	-0.1	0.1
Juvenile State Supervision	1.000	0.000	0.000	1.000	0.000	0.000	-0.1	0.1
Adult Jail	0.110	0.890	0.000	0.000	1.000	0.000	-0.1	0.1
Adult Local Supervision	0.270	0.730	0.000	0.000	1.000	0.000	-0.1	0.1
Adult State Prison	1.000	0.000	0.000	1.000	0.000	0.000	-0.1	0.1
Adult Post Prison Supervision	1.000	0.000	0.000	1.000	0.000	0.000	-0.1	0.1
Victim Costs (tangible)	n/a	n/a	n/a	n/a	n/a	n/a	-0.2	0.1
Victim Costs (intangible)	n/a	n/a	n/a	n/a	n/a	n/a	-0.2	0.1

[42] As noted, a few average cost figures are currently used in the model when marginal cost estimates cannot be reasonably estimated.

Police and Sheriff's Office Per-Unit Costs

This section describes the steps we use to estimate the annual marginal operating costs of local police agencies in Washington State, along with the expected long-run real rate of change in these costs. We also describe our estimate of the capital cost of police operations. All of these cost parameters are entered into the crime model, as shown in Exhibit 9.

Police Operating Costs. For an estimate of marginal operating costs of local police agencies, we conducted a time-series analysis of annual county-level data for police expenditures and arrests for all local police agencies in Washington's 39 counties. From the Washington State Auditor, local city and county police expenditure data were collected for 1994 to 2008, the earliest and latest years, as of winter 2010, electronically available. The Auditor's data for the expenses include all local police expenditures (Budget and Reporting System (BARS) code 521). We excluded the Crime Prevention (BARS 521.30) subcategory since it was an irregular expenditure. These nominal annual dollar amounts were adjusted to 2009 dollars using the United States Implicit Price Deflator for Personal Consumption Expenditures from the US Department of Commerce, as published and forecasted by the Washington Economic and Revenue Forecast Council.

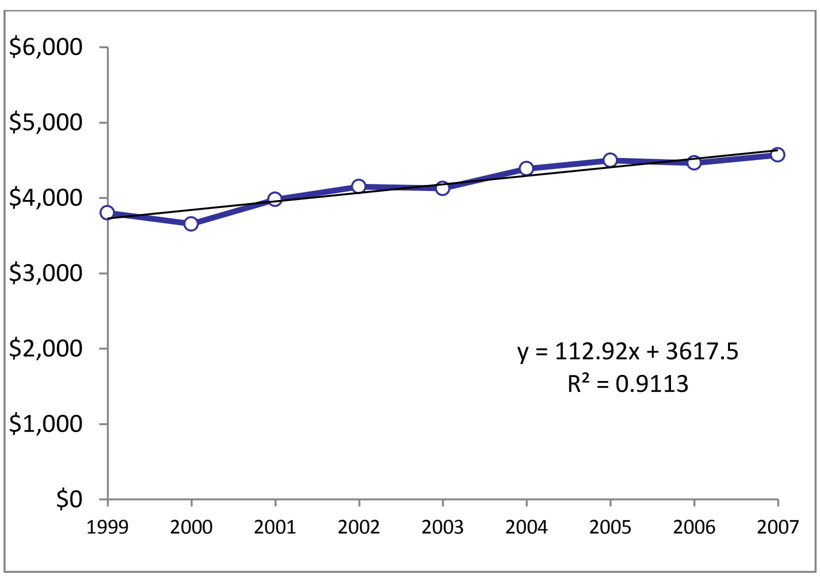
We also collected arrest information for Washington police agencies from the National Archive of Criminal Justice Data maintained by the University of Michigan.[43] Data were collected for calendar years 1994 to 2007, the earliest and latest years available as of December 2009. Arrest data for 1993 were unavailable on the Michigan website, thus limiting the number of years we could include in our analysis.

We aggregated the city and county expenditure and arrest data for individual police agencies to the county level to account for any jurisdictional overlap in county sheriffs' offices and city police units. We also aggregated to the county level because, over the years included in our analysis, some newly incorporated cities took on responsibilities formerly assigned to county sheriffs. Aggregating thus allowed for a more consistent cost-arrest data series for the years in our study. Since the latest arrest data were for 2007, the resulting balanced multiple time-series panel dataset initially consisted of 546 county-by-year observations.

We had to limit our analysis to 1999 to 2007 because visual inspection of the arrest data for years 1996 to 1998 revealed what appeared to be significant anomalies in the data, possibly due to reporting or other unknown factors during those years. Therefore, in our regression analyses, our dataset begins in 1999.

We computed the statewide average cost per arrest (in 2009 dollars) for 1999 to 2007 and plotted the results.

Exhibit 10
Average Police Costs per Arrest, 2009 Dollars
Calendar Years 1999 to 2007



[43]U.S. Department of Justice, Federal Bureau of Investigation. *Uniform crime reporting program data [United States]: County-level detailed arrest and offense data* [by year]. Ann Arbor, MI: Inter-university Consortium for Political and Social Research.

Over the entire 1999 to 2007 timeframe, the average statewide cost is $4,182 per arrest, in 2009 dollars. Over these years, there has been an upward trend in the inflation-adjusted costs. We computed an estimate of the average annual real escalation rate in costs by estimating a linear line (shown in the chart) for this series. From this line, we computed the predicted values for 1999 ($3,734) and 2007 ($4,638) and calculated the average escalation rate for the eight years, using the following formula, where FV is the 2007 estimated cost, PV is the 1999 estimate, and N is eight years.

$$(4.5)\ Rate = (FV/PV)^{1/N}$$

The annual rate of real escalation is 0.027. This point estimate is included as a parameter in the crime model, as shown in Exhibit 9.

Next, to estimate the marginal annual operating costs of police agencies, we conducted a time-series analysis of the panel data for Washington's 39 counties for 2001 to 2007. The restriction to 2001 (for the dependent variable) was because, after testing different lag structures of right-hand side variables, and to preclude using arrest data before 1999, our sample dependent variable began in 2001. Thus the balanced panel includes a total of 273 observations (39 counties for 7 years). We tested models where we disaggregated the arrest data into five types: arrests for murder, rape, robbery, aggravated assault, and all nonviolent arrests. After testing a variety of specifications, we did not find a specification with stable or intuitively reasonable results. At this time, we do not know if there are measurement errors in the arrest data, or if there are other tests to be explored. Therefore, we estimated a simple model with total arrests. This model, however, is unsatisfactory because it implies, for example, that the cost for an arrest for murder is the same as the cost for an arrest for burglary. We intend to examine the historical arrest data in greater detail so that a more intuitive equation can be estimated with disaggregated arrest types. The arrest data do not include the traffic operations of local police agencies. To capture this effect, data from the Washington State Administrative Office of the Courts were obtained on the number of traffic infraction filings in county courts.

In our time series analysis, we first tested each data series for unit roots. The data series include real police expenditures (M_POLICER), total arrests (A_TOT), and traffic infractions (TRAFFIC). If unit roots are present, then a simple regression in levels can produce spurious results.[44] We tested for unit roots with the Im, Pesaran, and Shin (IPS) panel unit root test for individual unit root processes.

- For the M_POLICER expenditure series, the IPS test without time trends failed to reject the null hypotheses that the series has a unit root (IPS p-value of 1.00). With time trends included, the IPS test continued to indicate a unit root (IPS p-value 0.34). In first-differences, on the other hand, the IPS test indicated a lack of a unit root (IPS p-value 0.000).
- For the two right-hand side variables, the IPS tests indicated a lack of a unit root for A_TOT (IPS p-value of 0.000), but a unit root for TRAFFIC (IPS p-value of 0.88).
- With the IPS test indicating a unit root in the dependent variable (M_POLICER), we proceeded to construct a model in first-differences.

We tested alternative lag specifications of the arrest and traffic variables. Our preferred model also included period and county fixed effects and a lagged dependent variable. The following results were obtained and the coefficients entered in the crime model, as shown in Exhibit 9. The sum of the arrest lags is $670. An identical model, but without including a right-hand side dependent variable, produced quite similar results.

[44] Wooldridge, J. M. (2009). *Introductory econometrics: A modern approach*. Mason, OH: South-Western Cengage Learning, p. 636.

Exhibit 11

Dependent Variable: M_POLICER-M_POLICER(-1)
Method: Panel Least Squares
Date: 04/17/10 Time: 10:29
Sample (adjusted): 2001 2007
Periods included: 7
Cross-sections included: 39
Total panel (balanced) observations: 273
White period standard errors & covariance (d.f. corrected)
WARNING: estimated coefficient covariance matrix is of reduced rank

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	956767.2	171084.1	5.592380	0.0000
M_POLICER(-1)-M_POLICER(-2)	-0.468607	0.097310	-4.815585	0.0000
A_TOT-A_TOT(-1)	240.6135	331.7045	0.725385	0.4690
A_TOT(-1)-A_TOT(-2)	428.8218	319.8050	1.340886	0.1813
TRAFFIC-TRAFFIC(-1)	109.2628	87.19574	1.253075	0.2115
TRAFFIC(-1)-TRAFFIC(-2)	123.4954	97.02971	1.272759	0.2044
TRAFFIC(-2)-TRAFFIC(-3)	350.3366	115.0134	3.046049	0.0026

Effects Specification

Cross-section fixed (dummy variables)
Period fixed (dummy variables)

R-squared	0.679778	Mean dependent var	1013022.
Adjusted R-squared	0.607657	S.D. dependent var	3244727.
S.E. of regression	2032410.	Akaike info criterion	32.05417
Sum squared resid	9.17E+14	Schwarz criterion	32.72847
Log likelihood	-4324.395	Hannan-Quinn criter.	32.32485
F-statistic	9.425402	Durbin-Watson stat	1.964607
Prob(F-statistic)	0.000000		

Police Capital Costs. An estimate of the capital costs used by local police to make arrests in Washington was calculated from capital expenditure data for local police agencies in Washington for 2006. These data were obtained from the United States Bureau of Justice Statistics annual survey: Justice Expenditure and Employment Extracts, 2006, published December 1, 2008 (NCJ 224394). Local government police capital expenditures in Washington were reported as $53,703,000 for 2006 (Table 4, Justice system expenditure by character, State and type of government, fiscal 2006). The total number of arrests in Washington during 2006 was 246,388, obtained from FBI's Uniform Crime Reports for 2006. Thus, the average police capital cost per arrest was $218 in 2006 dollars. This parameter was entered into the crime model, as shown in Exhibit 9, along with an assumed five-year financing for these police resources. In our crime model, the total capital cost per arrest is converted to an annualized capital payment, with equation 4.6, assuming a five-year financing term (n), the bond financing rate entered in the model (i), and setting PV equal to the capital cost per arrest converted to the base year dollars chosen for the model.

$$(4.6) \quad PMT = \frac{iPV}{1-(1+i)^{-n}}$$

Superior Courts and County Prosecutors Per-Unit Costs

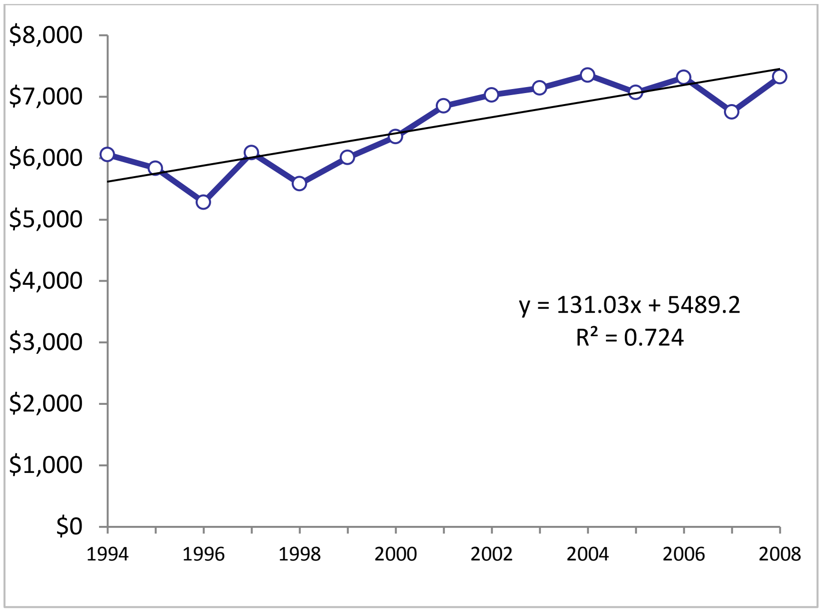
This section describes the steps we use to estimate marginal annual operating costs, and the long-run rate of change in these costs, of county superior courts and prosecutors in Washington State. Our focus is the cost of obtaining convictions in courts, so we combine court costs and prosecutor costs into one category to reflect the public costs to process cases through the courts that respond especially to felony crime. The cost parameters are entered into the crime model, as shown in Exhibit 9.

Court and Prosecutor Operating Costs. For an estimate of marginal operating costs of superior courts in Washington, we conducted a time series analysis of annual county-level data for court and prosecutor expenditures and court convictions for all local agencies in Washington's 39 counties. From the Washington State Auditor, local county court and prosecutor expenditure data were collected for calendar years 1994 to 2008, the earliest and latest years, as of winter 2010, electronically available. The Auditor's data for the expenses includes all local court and prosecutor expenditures (BARS code 512 for courts and BARS code 515 for prosecutors). The court data include the costs of administration (BARS 512.10), superior courts (BARS 512.20), and county clerks (BARS 512.30). For court expenditure data, we excluded district courts (BARS 512.40), since they do not process felony cases (the main subject of interest in our benefit-cost analysis) and expenditures for law library (BARS 512.70) and indigent defense (BARS 512.80); this latter category was excluded because the data were not available for the entire time frame under review. The prosecutor data include costs for administration-legal (515.10) and legal services (515.2). For prosecutor offices, we excluded facilities-legal services (515.50), consumer affairs-legal services (515.60), crime victim and witness program-legal (515.70), and child support enforcement-legal services (515.80). All nominal annual dollar amounts were adjusted to 2009 dollars using the United States Implicit Price Deflator for Personal Consumption Expenditures from the US Department of Commerce, as published and forecasted by the Washington Economic and Revenue Forecast Council.

We also collected court conviction and other case-processing information from the Washington State Administrative Office of the Courts. We collected statewide data for calendar years 1994 to 2008 and county-level data for calendar years 1997 to 2008, the earliest and latest years available as of December 2009.

We computed the statewide average cost per conviction (in 2009 dollars) for 1994 to 2008 and plotted the results.

Exhibit 12
Average Court Costs Per Conviction, 2009 Dollars
Calendar Years 1994 to 2008



Over the entire 1994 to 2008 timeframe, the average statewide cost is $6,557 per conviction, in 2009 dollars. Over these years, there has been an upward trend in the inflation-adjusted costs. We computed an estimate of the average annual real escalation rate in costs by estimating a linear line (shown in the chart) for this series. From this line, we computed the predicted values for 1994 ($5,625) and 2008 ($7,461) and calculated the average escalation rate for the 14 years, using equation 4.5, where FV is the 2008 estimated cost, PV is the 1994 estimate, and N is 14 years.

The annual rate of real escalation is 0.020. This point estimate is included as a parameter in the crime model, as shown in Exhibit 9.

Next, to estimate the marginal annual operating costs of courts, we conducted a time-series analysis of the panel data for Washington's 39 counties for 1999 to 2008. The restriction to 1999 (for the dependent variable) was because, after testing different lag structures of right-hand side variables, and since our county-level court data began in 1997, our sample dependent variable had to begin in 1999. Thus, the balanced panel includes a total of 390 observations (39 counties for 10 years). Conviction data were categorized into four types of violent convictions and one for all other convictions.

In our time-series analysis, we first tested each data series for unit roots. The six data series are: real total court expenditures (M_COURTALLR), convictions for homicide offenses (C_HOM), convictions for sex offenses (C_SEX), convictions for robbery offenses (C_ROB), convictions for aggravated assault offenses (C_ASSLT), and convictions for all non-violent offenses (C_NONVIOL). If unit roots are present, then a simple regression in levels can produce spurious results.[45] We tested for unit roots with the Im, Pesaran, and Shin (IPS) panel unit root test for individual unit root processes.

- For all of the variables, the IPS tests generally indicated a lack of unit roots. For example, IPS test without time trends rejected the null hypotheses that the series have unit roots (IPS p-values of 0.0028 for M_COURTALLR, 0.0000 for C_HOM, 0.0000 for C_SEX, 0.0000 for C_ROB, 0.0000 for C_ASSLT, 00.0006 for C_NONVIOL).
- With the IPS test indicating a lack of unit roots in the variables, we had the option to construct models in levels or first-differences.

[45] Ibid., p. 636.

We tested models both in levels and first-differences, along with alternative lag specifications for the conviction variables. Our preferred model was a first-difference model where we included lags of each of the violent felony conviction variables along with a variable for all other convictions, as well as county and time fixed effects. We also included a lagged dependent variable. This model produced coefficients for the violent conviction variables that made the most intuitive sense.

Exhibit 13

Dependent Variable: M_COURTALLR-M_COURTALLR(-1)
Method: Panel Least Squares
Date: 02/04/10 Time: 10:01
Sample (adjusted): 1999 2008
Periods included: 10
Cross-sections included: 39
Total panel (balanced) observations: 390
White diagonal standard errors & covariance (d.f. corrected)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	158006.5	86235.19	1.832274	0.0678
M_COURTALLR(-1)-M_COURTALLR(-2)	-0.113178	0.168569	-0.671403	0.5024
C_HOM(-1)-C_HOM(-2)	152377.9	125366.9	1.215456	0.2250
C_SEX(-1)-C_SEX(-2)	18770.28	11395.58	1.647154	0.1005
C_ROB(-1)-C_ROB(-2)	9865.480	29782.45	0.331252	0.7407
C_ASSLT(-1)-C_ASSLT(-2)	4876.710	9512.385	0.512670	0.6085
C_NONVIOL-C_NONVIOL(-1)	200.5611	1503.985	0.133353	0.8940

Effects Specification

Cross-section fixed (dummy variables)
Period fixed (dummy variables)

R-squared	0.209477	Mean dependent var	167352.1
Adjusted R-squared	0.084781	S.D. dependent var	2196761.
S.E. of regression	2101577.	Akaike info criterion	32.08216
Sum squared resid	1.48E+15	Schwarz criterion	32.63132
Log likelihood	-6202.021	Hannan-Quinn criter.	32.29985
F-statistic	1.679903	Durbin-Watson stat	1.973011
Prob(F-statistic)	0.003621		

Court Capital Costs. An estimate of the capital costs used by the court system in Washington was calculated from capital expenditure data for courts in Washington for 2006. These data were obtained from the United States Bureau of Justice Statistics annual survey: Justice Expenditure and Employment Extracts, 2006, published December 1, 2008 (NCJ 224394). Local government court expenditures in Washington were reported as $19,144,000 for 2006 (Table 4, Justice system expenditure by character, State and type of government, fiscal 2006). The total number of criminal (adult and juvenile) convictions in Washington during 2006 was 51,709, obtained from the Washington State Administrative Office of the Courts. Thus, the average court capital cost per conviction was $370 in 2006 dollars. This parameter was entered into the crime model, as shown in Exhibit 9, along with an assumed 20-year financing period. In our crime model, the total capital cost per conviction is converted to an annualized capital payment, with equation 4.6, assuming a 20-year financing term (n), the bond financing rate entered in the model (i), and setting PV equal to the capital cost per conviction converted to the base year dollars chosen for the model.

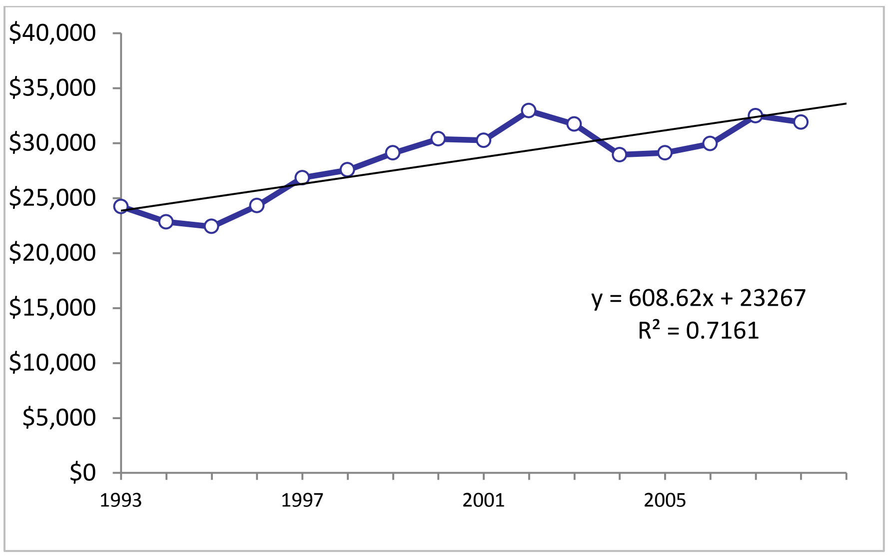
Local Adult Jail Per-Unit Costs

This section describes the steps we use to estimate marginal annual jail operating costs, and the long-run rate of change in these costs, of the county-run adult jail system in Washington State. We also describe our estimate of the capital cost per jail bed. All of these cost parameters are entered into the crime model, as shown in Exhibit 9. In WSIPP's model, two types of users of local county-run adult jails are analyzed: convicted felons who serve both pre-sentence and post-sentence time at a local jail, and felons who serve pre-sentence time at local jails and post-sentence time at a state institution. WSIPP assumes the same annualized per-day jail cost for both these events.

Jail Operating Costs. For an estimate of marginal operating costs of county jails, we conducted a time-series analysis of annual county-level data for jail expenditures and average jail population for each of Washington's 39 counties for calendar years 1995 to 2008. Thus, the balanced multiple time series panel dataset consists of 546 observations. From the Washington State Auditor, local jail expenditure data for counties were collected for 1993 to 2008, the earliest and latest years, as of winter 2010, electronically available. The Auditor's data for the expenses includes all local jail expenditures (BARS code 527) except local probation costs (BARS code 527.40). These nominal annual dollar amounts were adjusted to 2009 dollars (JAILREAL) using the United States Implicit Price Deflator for Personal Consumption Expenditures from the US Department of Commerce, as published and forecasted by the Washington Economic and Revenue Forecast Council. The jail average daily population data (JAILADP) was obtained from the Washington Association of Sheriffs and Police Chiefs.

We computed the statewide average cost per jail ADP (in 2009 dollars) and plotted the results.

Exhibit 14
Average County Jail ADP Costs, 2009 Dollars
Fiscal Years 1993 to 2008



Over the entire 1993 to 2008 timeframe, the average statewide cost is $28,900 per ADP, in 2009 dollars. Over these years, there has been an upward trend in the inflation-adjusted costs. We computed an estimate of the average annual real escalation rate in costs by estimating a linear line (shown of the chart) for this series. From this line, we computed the predicted values for 1993 ($23,897) and 2008 ($33,035) and calculated the average escalation rate for the 15 years, using equation 4.5, where FV is the 2008 estimated cost, PV is the 1993 estimate, and N is 15 years.

The annual rate of escalation is 0.022. This point estimate is included as a parameter in the crime model, as shown in Exhibit 9.

To estimate the marginal annual operating costs of county jails, we conducted a time-series analysis of the panel data for Washington's 39 counties for 1993 to 2008. Thus the balanced panel includes a total of 546 observations. First, we tested each data series (JAILADP and JAILREAL) for unit roots. If unit roots are present, then a simple regression in levels of two unit root series can produce spurious results.[46] We tested for unit roots with a panel unit root test, the Im, Pesaran, and Shin (IPS) test for individual unit root processes.

- For the JAILREAL expenditure series, the test without time trends failed to reject the null hypotheses that the series has a unit root (IPS p-value of 1.00). With time trends included, the IPS test continued to indicate a unit root (p-value 0.713). In first-differences, the test indicated a lack of a unit root (IPS p-value 0.000).
- For the JAILADP series, the IPS test without time trends failed to reject the null hypotheses that the series has a unit root (IPS p-value of 0.975). With time trends included, the IPS test continued to indicate a unit root (p-value 0.582). In first-differences, the test indicated a lack of a unit root (IPS p-value 0.000).
- With the IPS test indicating unit roots in both JAILREAL and JAILADP series, and no unit roots in first-differences, we proceeded to construct a model in first-differences.

[46] Ibid., p. 636.

Since the two series have unit roots, we tested to determine if the two series together are cointegrated.[47] We used two versions of a panel cointegration test in EVIEWS. Both the Pedroni Engle-Granger test (p-value 0.000) and the Kao Engle-Granger test (p-value 0.000) rejected the null hypothesis of no cointegration. We concluded that the two series together are I(0) cointegrated.

Since the two unit root series are cointegrated, we estimated an error correction model in first-differences. We tested alternative lag specifications of the JAILADP variable and concluded that three lags were appropriate. For the error correction term, we computed a cointegrating parameter from a simple model of: JAILREAL = a + b(JAILADP).

The sum of the three ADP variables was $21,469. The F-test of joint significance for the three ADP variables is marginally significant with a p-value of 0.113. The short-run marginal cost from the regression is the first lag term ($3,457). We included cross-section (county) and period (year) fixed effects in the specification. We also included a lagged dependent variable on the right-hand side. Without this variable, the sum of the three ADP coefficients totaled $37,637, an amount that seemed much higher than we expected. Thus, we included the lagged dependent variable in the model.[48]

Exhibit 15

Dependent Variable: JAILREAL-JAILREAL(-1)
Method: Panel Least Squares
Date: 01/21/10 Time: 14:36
Sample (adjusted): 1995 2008
Periods included: 14
Cross-sections included: 39
Total panel (balanced) observations: 546
White diagonal standard errors & covariance (d.f. corrected)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-682109.7	264036.1	-2.583395	0.0101
JAILREAL-1)-JAILREAL(-2)	0.359767	0.089133	4.036304	0.0001
JAILADP-JAILADP(-1)	3456.648	3050.223	1.133244	0.2577
JAILADP(-1)-JAILADP(-2)	8348.148	6128.536	1.362177	0.1738
JAILADP(-2)-JAILADP(-3)	9663.879	4591.016	2.104954	0.0358
JAILRREAL(-1)-39640.36*JAILADP(-1)	-0.266495	0.089148	-2.989351	0.0029

Effects Specification

Cross-section fixed (dummy variables)
Period fixed (dummy variables)

R-squared	0.683040	Mean dependent var	439983.7
Adjusted R-squared	0.646742	S.D. dependent var	2286829.
S.E. of regression	1359189.	Akaike info criterion	31.18121
Sum squared resid	9.03E+14	Schwarz criterion	31.63038
Log likelihood	-8455.470	Hannan-Quinn criter.	31.35680
F-statistic	18.81750	Durbin-Watson stat	2.024971
Prob (F-statistic)	0.000000		

Jail Capital Costs. Local adult jail capital costs for new beds were estimated from an informal internet review of current estimates for a variety of new jails around the country. We placed the estimate at $150,000 capital cost per county jail bed. In our crime model, the total capital cost per bed is converted to an annualized capital payment, with equation 4.6, assuming a 25-year financing term (n), the bond financing rate entered in the model (i), and setting PV equal to the capital cost per bed converted to the base-year dollars chosen for the model.

[47] Ibid., p. 639.
[48] We also ran the preferred model shown above, but without the error correction. The coefficients from the three ADP variables totaled $44,980—again, this sum seems too large based on prior expectations.

Local Juvenile Detention and Probation Per-Unit Costs

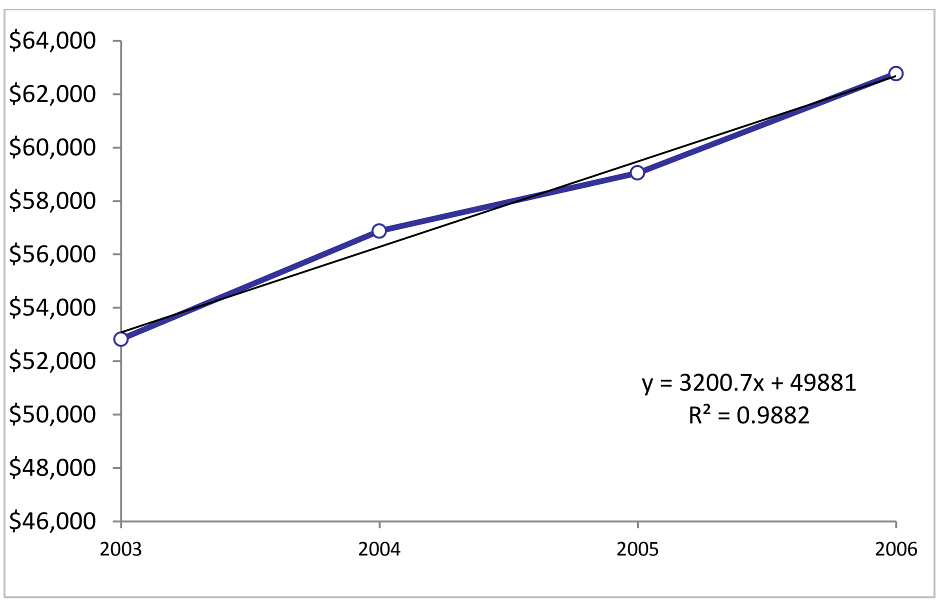
This section describes the steps we use to estimate marginal annual detention operating costs, and the long-run rate of real (inflation-adjusted) change in these costs of county-run juvenile detention facilities in Washington. We also describe our estimate of the capital cost per detention bed, as well as our estimate for the marginal annual costs of local juvenile probation and the real rate of annual escalation in these costs. All of these estimated cost parameters are entered into the crime model, as shown in Exhibit 9.

Detention Operating Costs. For an estimate of the marginal operating cost of state juvenile offender institutions, we conduct a time-series analysis of annual data for detention expenditures and average daily admissions to juvenile detention facilities in Washington. From the Washington State Auditor, local juvenile detention operating expenditure data for counties were collected for 1993 to 2008, the earliest and latest years electronically available, as of winter 2010. The Auditor's data for the expenses include the categories for residential care and custody (BARS 527.60) and juvenile facilities (BARS 527.80). Unfortunately, visual inspection of these historical data revealed significant problems and gaps, apparently caused by inconsistent reporting. We concluded that a consistent series could only be used for four years, 2003 to 2006. These nominal annual dollar amounts were adjusted to 2009 dollars using the United States Implicit Price Deflator for Personal Consumption Expenditures from the US Department of Commerce, as published and forecasted by the Washington Economic and Revenue Forecast Council.

To our knowledge, there is not a consistent statewide data series available for the average daily population of the county juvenile detention facilities. Instead, we collected annual admission data for the juvenile facilities; this information is collected and published by the Washington State Governor's Juvenile Justice Advisory Committee. From other data we have analyzed previously, it appears the average length of stay of a juvenile detention admission is about 12 days. Using this figure, along with the actual admission data, we estimated the ADP of the facilities statewide.

We computed the average costs per institutional ADP (in 2009 dollars) and plotted these data on this chart.

Exhibit 16
Average Local Juvenile Detention ADP Costs,
2009 Dollars, Fiscal Years 2003 to 2006



Over the 2003 to 2006 timeframe, the average annual cost is $57,727 per ADP, in 2009 dollars. Over these years, there has been an upward trend in the inflation-adjusted costs. We computed an estimate of the average annual real escalation rate in costs by estimating a linear line (shown in the chart) for this series. From this line, we computed the predicted values for 2003 ($53,131) and 2006 ($62,742) and calculated the average escalation rate for the three years, using formula 4.5, where FV is the 2006 estimated cost, PV is the 2003 estimate, and N is three years.

The annual rate of real escalation is 0.057. This point estimate is included as a parameter in the crime model, as shown in Exhibit 9. Because this is a high escalation rate, it will be important to seek additional information for this parameter.

Next, to estimate the marginal annual operating costs of police agencies, we conducted a time-series analysis of the panel data for Washington's 39 counties for 2003 to 2006. Because of the reasons mentioned above regarding the lack of a longer time series, we could not conduct unit root tests for these data. Since a regression in levels indicated a very high R-squared, and this often can indicate unit roots, and since so many of our other analyses of criminal justice data have revealed unit roots, we proceeded to construct a first-difference regression model.

We tested alternative lag specifications of the admission data. Our preferred model contained two lags and also a lagged dependent variable. Because of the lagging and, unfortunately, the already short time series, the model only had two periods for the 20 counties in Washington with juvenile detention facilities. The sum of the two admission coefficients is $667. We converted this to an estimate of the annual marginal cost per ADP by, again, assuming a 12-day average length of stay. The result was an estimate of $20,293 per annual ADP for juvenile detention marginal operating expenditures, in 2009 dollars. The following are the regression results obtained to support these calculations.

Exhibit 17

Dependent Variable: JUVDETREAL-JUVDETREAL(-1)
Method: Panel Least Squares
Date: 02/05/10 Time: 17:16
Sample (adjusted): 2005 2006
Periods included: 2
Cross-sections included: 20
Total panel (balanced) observations: 40
White cross-section standard errors & covariance (d.f. corrected)
WARNING: estimated coefficient covariance matrix is of reduced rank

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	80820.93	8253.006	9.792908	0.0000
JUVDETREAL(-1)-JUVDETREAL(-2)	-0.139491	0.082108	-1.698865	0.0980
JUVDETADM-JUVDETADM(-1)	445.0912	246.1837	1.807964	0.0790
JUVDETADM(-1)-JUVDETADM(-2)	222.0772	57.98376	3.829989	0.0005

R-squared	0.087247	Mean dependent var	44115.96
Adjusted R-squared	0.011185	S.D. dependent var	333851.7
S.E. of regression	331979.4	Akaike info criterion	28.35817
Sum squared resid	3.97E+12	Schwarz criterion	28.52706
Log likelihood	-563.1635	Hannan-Quinn criter.	28.41924
F-statistic	1.147044	Durbin-Watson stat	2.026817
Prob(F-statistic)	0.343320		

Local Detention Capital Costs. Per-bed capital costs for a new detention facility would run $200,000 per bed.[49] In our crime model, the total capital cost per arrest is converted to an annualized capital payment, with equation 4.6, assuming a 25-year financing term (n), the bond financing rate entered in the model (i), and setting PV equal to the capital cost per bed converted to the base-year dollars chosen for the model.

Local Juvenile Probation Per-Unit Costs. We searched for longitudinal time-series data to estimate the average annual cost of county-run juvenile probation services in Washington. Unfortunately, we did not locate a consistent set of expenditure information or average daily caseload information that would have allowed us to perform a valid time-series analysis. The expenditure data from the Washington State Auditor contain a considerable number of county jurisdictions that do not report, every year, their juvenile court expenditures. And, as far as we know, there is not a data source for the average daily juvenile court probation caseloads in Washington.

[49] Capital costs for a typical new local juvenile detention facility were estimated from personal communication with Washington's Juvenile Rehabilitation Administration staff.

Therefore, we estimated marginal juvenile court probation costs with the following procedures.

- From the State Auditor, we collected statewide juvenile court probation expenditure data for calendar year 2008, the latest year reported as of March 2010. These data appear to be reasonably complete with the exception of Snohomish County that did not report juvenile county probation expenditures that year. The total reported expenditures for juvenile probation for the state was $29,203,723 for 2008. Again, this figure does not include Snohomish County.
- From the Administrative Office of the Courts, we collected the reported number of juvenile court community supervision sentences and sentences with detention and community supervision for 2008. The total was 5,660.
- From a WSIPP survey of juvenile court activities in 1995, we calculated that the average length of stay on juvenile court probation in Washington is 6.8 months.[50]
- We then estimated the 2008 average daily probation caseload of juvenile courts as 3,207 (5,660 times 6.8 divided by 12 months).
- We adjusted the statewide average daily caseload to remove Snohomish County by subtracting an estimate of Snohomish's average daily caseload. Snohomish had 705 juvenile court community supervision sentences and sentences with detention and community supervision in 2008. An estimate of the average daily caseload in Snohomish for 2008 was 400 (705 times 6.8 divided by 12 months), assuming the same 6.8-month average length of stay on juvenile court probation. Thus, after removing Snohomish, an estimate of the adjusted statewide average daily probation caseload was 2,808 in 2008.
- We then computed the average expenditure per average annual daily caseload to be $10,401 ($29,203,723 divided by 2,808).
- From this estimate of the *average* expenditure per average annual caseload, we estimated the *marginal* expenditure per average annual caseload. We found from our time-series analysis of the community supervision costs from the Department of Corrections that the ratio of marginal costs to average costs was 0.50 (see local community supervision section where marginal DOC community supervision costs are estimates as $1,861 and average costs are $3,707). Multiplying $10,401 by 0.50 provides an estimate, $5,200 in 2008 dollars, of the marginal cost per average annual juvenile court caseload. This estimate is included as a parameter in the crime model, as shown in Exhibit 9.

State Juvenile Rehabilitation Administration (JRA) Per-Unit Costs

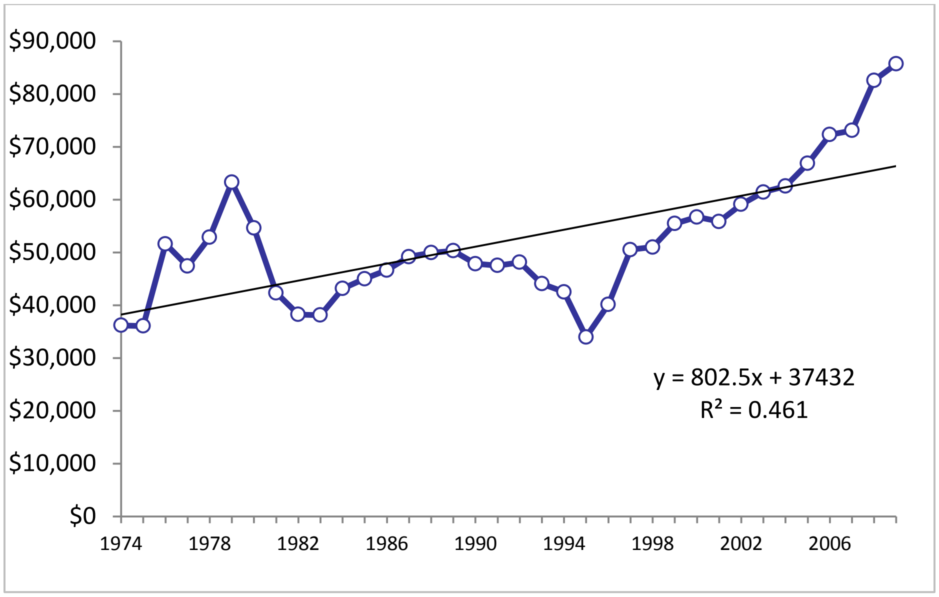
This section describes the steps we use to estimate marginal annual institution operating costs, and the long-run rate of real (inflation-adjusted) change in these costs, of the Washington State Juvenile Rehabilitation Administration (JRA). JRA is Washington's state juvenile justice agency; juvenile offenders are sentenced to JRA based on Washington's sentencing laws and practices. We also describe our estimate of the JRA capital cost per institutional bed as well as our estimate for the marginal annual costs of community supervision for juvenile parole supervision in Washington, and the real rate of annual escalation in these costs. All of these estimated cost parameters are entered into the crime model, as shown in Exhibit 9.

Institutional Operating Costs. For an estimate of the marginal operating costs of state juvenile offender institutions, we conducted a time-series analysis of annual data for institutional expenditures and average daily institutional population for JRA for fiscal years 1974 to 2009. The expenditure data were obtained from the Washington State's Legislative Evaluation and Accountability Program (LEAP) for Agency 300 (Juvenile Rehabilitation Administration) for code 2000 (institutional services). The LEAP data series for JRA begins in fiscal year 1974. We converted the expenditure data to 2009 dollars (JRAREAL) using the United States Implicit Price Deflator for Personal Consumption Expenditures from the US Department of Commerce, as published and forecasted by the Washington Economic and Revenue Forecast Council. The average daily population for JRA institutions (JRAADP) series is from the Washington State Caseload Forecast Council for Fiscal Years 1997 to 2009, with data from 1974 to 1996 taken from annual reports of the Governor's Juvenile Justice Advisory Committee and data from various issues of the Databook series published by the Washington State Office of Financial Management.

We computed the average costs per institutional ADP (in 2009 dollars) and plotted these data in Exhibit 18.

[50] Burley, M. & Barnoski, R. (1997). *Washington State juvenile courts: Workloads and costs.* (Document No. 97-04-1201). Olympia: Washington State Institute for Public Policy, Table 2.

Exhibit 18
Average JRA Institution ADP Costs, 2009 Dollars
Fiscal Years 1974 to 2009



Over the entire 1974 to 2009 timeframe, the average cost is $51,716 per ADP, in 2009 dollars. Over these years, there has been an upward trend in the inflation-adjusted costs. We computed an estimate of the average annual real escalation rate in costs by estimating a linear line (shown in the chart) for this series. From this line, we computed the predicted values for 1974 ($38,274) and 2009 ($66,379) and calculated the average escalation rate for the 35 years, using formula 4.5, where FV is the 2009 estimated cost, PV is the 1974 estimate, and N is 35 years.

The annual rate of escalation is 0.016. This point estimate is included as a parameter in the crime model, as shown in Exhibit 9. The data plotted on the chart reveals that in the last five years, the growth in real average costs has been on a steeper incline compared with the annual growth rate over the entire period of record. Thus, our estimate of 0.016 may be on the low side if recent trends persist.

To estimate the marginal annual operating cost of a state institutional bed, we conducted a time-series analysis of these data. First, we tested each data series (JRAADP and JRAREAL) for unit roots. If unit roots are present, then a simple regression in levels of two unit root series can produce spurious results.[51] We tested for unit roots with an Augmented Dickey-Fuller (ADF) test.

- For the JRAREAL expenditure series, the ADF test failed to reject the null hypotheses that the series has a unit root, with p-values of 0.511 without a time trend and 0.620 with a time trend, indicating a unit root with both tests. In first-differences, on the other hand, the ADF p-value for the JRAREAL series is 0.000.
- For the JRAADP series, the p-values were 0.299 without a time trend and 0.760 with a time trend, indicating a unit root in both tests. In first-differences, the ADF p-value for the JRAADP series is 0.049.
- With both JRAREAL and JRAADP series indicating unit roots in levels and no unit roots in first-differences, we proceeded to construct a model in first-differences.

Since the two series have unit roots, we tested to determine if the two series together are cointegrated.[52] We used an Engle-Granger test to determine whether the residuals from a cointegrating regression of the two series are integrated of order 1 (i.e., I(1), unit root). The resulting tau-statistic from the regression was -1.03, which is well below the Engle-Granger critical value of -3.9 (p-value 0.01) for the null hypothesis that the residual series has a unit root. Therefore, this test did not reject the null hypothesis that the two series, jointly, have a unit root. We concluded that the two series together are I(1) and, therefore, not I(0) cointegrated.

[51] Wooldridge (2009): p. 636.
[52] Ibid., p. 639.

We then computed a first-difference model with three lags on the first-differenced JRAADP variables and obtained the following result:

Exhibit 19

Dependent Variable: JRAREAL-JRAREAL(-1)
Method: Least Squares
Date: 01/20/10 Time: 15:53
Sample (adjusted): 1975 2009
Included observations: 35 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-321480.3	928044.0	-0.346406	0.7315
JRAADP-JRAADP(-1)	5845.823	16565.04	0.352901	0.7266
JRAADP(-1)-JRAADP(-2)	28438.73	18767.99	1.515279	0.1402
JRAADP(-2)-JRAADP(-3)	2458.799	13179.94	0.186556	0.8533
RPCI(-1)-RPCI(-2)	2276.323	888.6560	2.561534	0.0157

R-squared	0.257160	Mean dependent var	1038534.
Adjusted R-squared	0.158115	S.D. dependent var	5199909.
S.E. of regression	4771140.	Akaike info criterion	33.72563
Sum squared resid	6.83E+14	Schwarz criterion	33.94783
Log likelihood	-585.1986	Hannan-Quinn criter.	33.80233
F-statistic	2.596387	Durbin-Watson stat	2.090018
Prob(F-statistic)	0.056213		

After testing different model specifications, our preferred model includes three lagged first-difference JRAADP variables and a first-differenced covariate (RPCI, real per capita income). We examined multiple lags in the JRAADP variables and three lags seemed appropriate. The sum of the three lagged coefficients was $36,743, in 2009 dollars. This is our estimate of the marginal operating cost of an annual JRA bed.[53] The three ADP variables were jointly significant with a p-value on the F test of .0473. The short-run marginal cost from the regression is the first lag term ($5,846).

JRA Capital Costs. JRA capital costs for typical new institutional beds were estimated from personal communication with JRA staff. Per-bed capital costs for a new medium secure facility would run $125,000 to $175,000 per bed. In our crime model, the total capital cost per arrest is converted to an annualized capital payment, with equation 4.6, assuming a 25-year financing term (n), the bond financing rate entered in the model (i), and setting PV equal to the capital cost per bed converted to the base year dollars chosen for the model.

JRA Parole Costs. We were unable to obtain a long-term data set to analyze the marginal cost of JRA parole services. The electronic data for parole expenditures were only available starting in fiscal year 2000 and, beginning in fiscal year 2006, there was a significant accounting change that rendered the post-2005 data unusable for measuring parole expenditures. We do have consistent parole average daily population data from 1981 through 2009. We intend to obtain earlier expenditure data which may allow a regression analysis. In the meantime, we calculated an average parole cost by summing inflation-adjusted JRA parole costs from 2000 to 2005—$43,004,688 (in 2009 dollars). The sum of the average daily parole caseloads during these same years was 5,481. Thus, the average annual expenditure per parole average daily population is $7,847, in 2009 dollars. From this estimate of the average expenditure per average annual caseload, we estimated the marginal expenditure per average annual caseload. We found from our time-series analysis of the community supervision costs of the Department of Corrections that the ratio of marginal costs to average costs was 0.50. Multiplying $7,847 by 0.50 provides an estimate, $3,923 in 2009 dollars, of the marginal cost per average annual JRA parole caseload. This estimate is included as a parameter in the crime model, as shown in Exhibit 9.

[53] We also estimated a model identical to our preferred model but with a lagged first-differenced dependent variable on the right-hand side. The sum of the three ADP coefficients was $39,138, only slightly larger than our preferred model. For purposes of our benefit-cost model, which is to compute benefit-cost estimates of evidence-based programs that reduce crime, our preference is to use the slightly more cautious estimate.

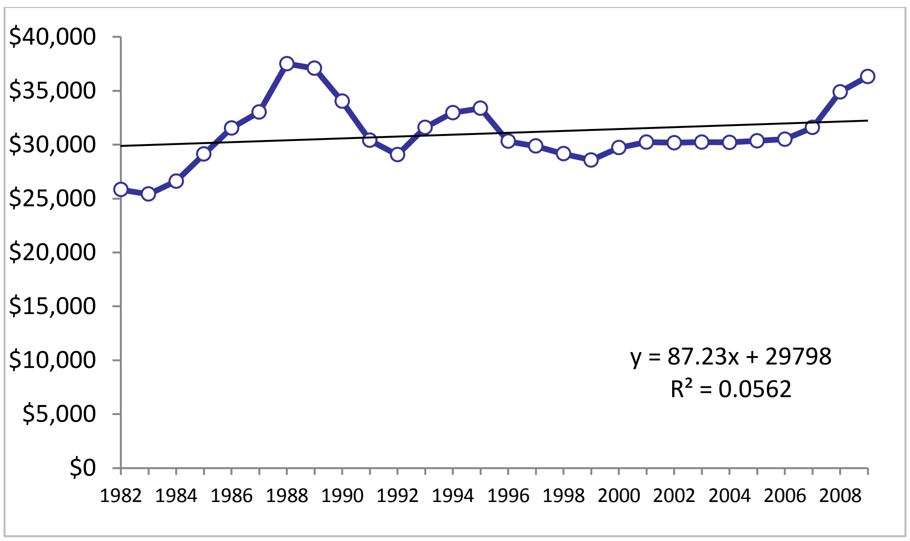
State Department of Corrections (DOC) Per-Unit Costs

This section describes the steps we use to compute estimates of Washington Department of Corrections' marginal annual prison operating costs and the long-run rate of change in these costs. We also provide our estimate of the capital cost of a prison bed. Additionally, we describe our estimate for the annual cost of community supervision for adult felony offenders in Washington, and the real rate of annual escalation in this cost.

Prison Operating Costs. For prison operating costs, we analyzed annual data for DOC institutional expenditures and average daily prison population for fiscal years 1982 to 2009. The expenditure data were obtained from LEAP for Agency 310 (Department of Corrections) for code 200 (correctional expenditures); the LEAP data series for DOC begins in fiscal year 1982. The "correctional expenditures" category pertains to operating expenses for running the state's prison system, not the community corrections system. We converted the expenditure data to 2009 dollars using the United States Implicit Price Deflator for Personal Consumption Expenditures from the US Department of Commerce, as published and forecasted by the Washington Economic and Revenue Forecast Council. The average daily prison population (ADP) series is from the Washington State Caseload Forecast Council for fiscal years 1993 to 2009, with data for earlier years taken from various issues of the Databook series published by the Washington State Office of Financial Management.

We computed the average cost per prison ADP (in 2009 dollars) for 1982 to 2009 and plotted the results.

Exhibit 20
Average DOC ADP Prison Costs, 2009 Dollars
Fiscal Years 1982 to 2009



Over the entire 1982 to 2009 timeframe, the average cost is $31,446 per ADP, in 2009 dollars. Over these years, there has been a slight upward trend in the inflation-adjusted per-unit costs, as revealed by the linear regression line shown in Exhibit 20. To compute an estimate of the long-run growth rate in real cost per average daily population, we calculated the predicted values from the regression line for 1982 ($29,915) and 2009 ($32,266) and calculated the annual rate of escalation for the 27 years using equation 4.5, where FV is the 2009 cost estimate, PV is the 1982 estimate, and N is 27 years.

The annual rate of real escalation in average costs is 0.003. This point estimate is included as a parameter in the crime model, as shown in Exhibit 9.

To estimate marginal prison operating costs, we conducted a time-series analysis of total annual real operating costs (DOCREAL) and the total annual prison average daily population (DOCADP). First, we tested each data series for unit roots. If unit roots are present, then a simple regression in levels of two unit root series can produce spurious results.[54] We tested for unit roots with an Augmented Dickey-Fuller (ADF) test.

- For the DOCREAL expenditure series, the ADF test failed to reject the null hypotheses that the series has a unit root with p-values of 0.9999 without a time trend and 0.9978 with a time trend. In first-differences, on the other hand, the ADF p-value for the DOCREAL series was 0.0146, indicating a lack of a unit root in a first-differenced data series.
- For the DOCADP series, the p-values for the ADF test were 0.8668 without a time trend and 0.2744 with a time trend; both tests indicate that the DOCADP series in levels has a unit root. In first-differences, the ADF p-value for the DOCADP series was 0.0458 indicating a lack of a unit root in first-differences.
- With both DOCREAL and DOCADP series indicating unit roots in levels and no unit roots in first-differences, we proceeded to construct models in first-differences.[55]

Assuming the two series have unit roots, we tested to determine if the two series together are cointegrated.[56] We used an Engle-Granger test to determine whether the residuals from the cointegrating regression were integrated of an order of 1 (i.e., I(1), a unit root). The resulting tau-statistic from the regression was -2.667, which is below the Engle-Granger critical value of -3.9 (p-value 0.01). Therefore, this test did not reject the null hypothesis that the two series, jointly, have a unit root. We concluded that the two series together are I(1) and, therefore, not cointegrated.

Exhibit 21

Dependent Variable: DOCREAL-DOCREAL(-1)
Method: Least Squares
Date: 01/18/10 Time: 16:09
Sample (adjusted): 1983 2009
Included observations: 27 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 3.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	12790705	6212729.	2.058790	0.0521
DOCADP-DOCADP(-1)	4495.187	6295.155	0.714071	0.4830
DOCADP(-1)-DOCADP(-2)	-4288.905	5011.822	-0.855758	0.4018
DOCADP(-2)-DOCADP(-3)	6745.884	3736.465	1.805419	0.0854
DOCADP(-3)-DOCADP(-4)	6968.766	2879.800	2.419879	0.0247
RPCI(-1)-RPCI(-2)	2355.135	3505.699	0.671802	0.5090

R-squared	0.128695	Mean dependent var	21124103
Adjusted R-squared	-0.078759	S.D. dependent var	14953657
S.E. of regression	15531362	Akaike info criterion	36.14775
Sum squared resid	5.07E+15	Schwarz criterion	36.43571
Log likelihood	-481.9946	Hannan-Quinn criter.	36.23338
F-statistic	0.620356	Durbin-Watson stat	1.290263
Prob(F-statistic)	0.685814		

Since the two unit root series are not jointly cointegrated, we did not estimate an error correction model and, instead, estimated a first-difference model.[57] The following results were obtained.

After testing different model specifications, our preferred model includes regressors with four lagged first-difference DOCADP variables and a first-differenced covariate (RPCI, real per capita income). We examined different numbers of lags in the DOCADP variables, and four lags seemed appropriate empirically and logically given our knowledge of state budgeting processes. The four DOCADP lags are jointly statistically significant (F test p-value 0.0085). The short-run marginal cost from the regression is the first lag term ($4,495).

[54] Wooldridge (2009): p. 636.
[55] Ibid., p. 643.
[56] Ibid., p. 639.
[57] Ibid., p. 643.

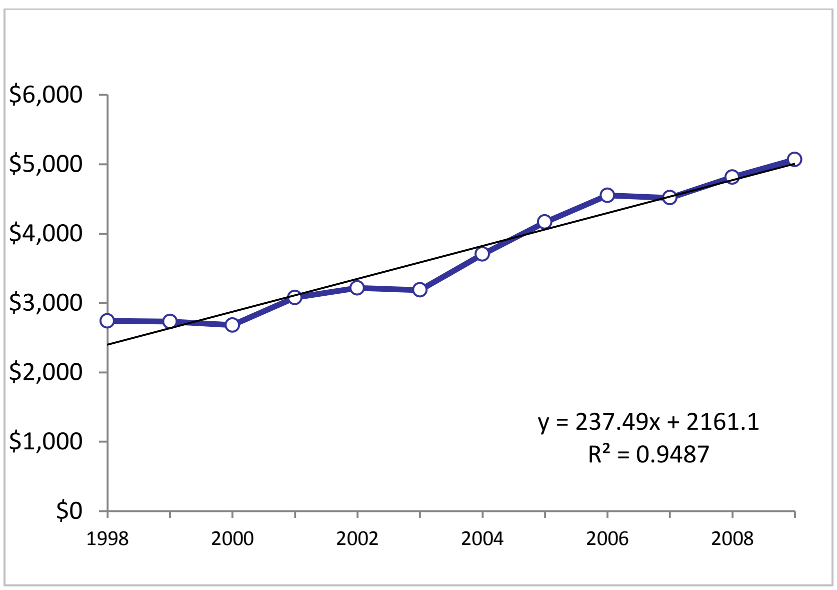
The sum of the four DOCADP distributed lags (the long-run multiplier) is $13,921. This figure, $13,921 per ADP (in 2009 dollars), represents our preferred estimate of the long-run incremental expenditures to DOC for a year in prison. This point estimate is included as a parameter in the crime model, as shown in Exhibit 9.[58]

The readily available annual time series for this analysis, unfortunately, was limited from 1982 to 2009, because expenditure data (DOCREAL) were only available from 1982 onward. We reviewed this marginal cost per prison ADP with legislative and executive fiscal staff to determine the accuracy of our estimate in the budgeting world. It was agreed upon that the marginal cost per prison ADP is $12,722.

Prison Capital Costs. DOC capital costs for new institutional beds were estimated. Capital cost estimates for the relatively new Coyote Ridge medium security facility in Washington were obtained from legislative fiscal staff. The 2,048 bed facility cost $232,118,000 (thus, a per-bed cost of $113,339) and was completed in 2008. We recorded this per-bed cost figure as 2007 dollars since it is likely that was when most of the construction dollars were spent. This point estimate is included as a parameter in the crime model, as shown in Exhibit 9. In our crime model, the total construction costs per-bed are converted to an annualized capital payment, with equation 4.6, assuming a 25-year financing term, the bond financing rate entered in the model, and setting PV equal to the per-bed construction cost converted to the base year dollars chosen for the model.

Community Supervision Operating Costs. We analyzed Department of Corrections' community supervision cost for all felony offenders on active supervision regardless of sentence type (prison or jail). For community supervision costs, we analyzed annual data for DOC community supervision expenditures and average daily community population for Fiscal Years 1998 to 2009. The expenditure data were obtained from LEAP for Agency 310 (Department of Corrections) for code 300 (community supervision); the LEAP data series for DOC begins in fiscal year 1982. Community supervision population data were obtained from the Washington Caseload Forecast Council, which maintains data back to fiscal year 1998. We calculated annual cost per average daily community population and converted to 2009 dollars using the aforementioned price index. The average community supervision cost over the 1998 to 2009 period is $3,657.

Exhibit 22
Average DOC Average Daily Community Supervision Costs, 2009 Dollars, Fiscal Years 1998 to 2009



[58] As an additional test, we ran our preferred model with a lagged first difference dependent variable on the right-hand side of the equation. The results were somewhat similar to our preferred model (e.g., the sum of the three positive lagged DOCADP coefficient was $15,413, but the three coefficient together were only marginally significant with a F-test p-value of 0.1111).

Over the 1998 to 2009 period, there was a significant upward trend in the inflation-adjusted per-unit costs, as revealed by the linear regression line shown in Exhibit 22. To compute an estimate of the long-run growth rate in real cost per average daily population, we calculated the predicted values from the regression line for 1998 ($2,399) and 2009 ($4,773) and calculated the annual rate of escalation for the 11 years using equation 4.5 where FV is the cost estimate for 2009, PV is the estimate for 1998, and N is 11 years.

The annual rate of real escalation in average costs is 0.064. This point estimate is included as a parameter in the crime model, as shown in Exhibit 9. This estimate seems high, and it will be useful to monitor actual expenditure trends in the years ahead.

To estimate marginal community supervision operating costs, we conducted a time-series analysis of total annual real operating costs (DOCCSREAL) and the total annual community supervision average daily population (DOCCSADP). First, we tested each data series for unit roots. If unit roots are present, then a simple regression in levels of two unit root series can produce spurious results.[59] We tested for unit roots with an Augmented Dickey-Fuller (ADF) test.

- For the DOCCSREAL expenditure series, the ADF test failed to reject the null hypotheses that the series has a unit root with p-values of 0.8446 without a time trend, but was significant at 0.0276 with a time trend. In first-differences, on the other hand, the ADF p-value for the DOCCSREAL series was 0.0263, indicating a lack of a unit root in a first-differenced data series.
- For the DOCCSADP series, the p-values for the ADF test were 0.2243 without a time trend and 0.2682 with a time trend; both tests indicate that the DOCCSADP series in levels has a unit root. In first-differences, the ADF p-value for the DOCCSADP series was 0.1318 indicating, marginally, a lack of a unit root in first-differences.
- With both DOCCSREAL and DOCCSADP series indicating, generally, unit roots in levels (with the exception of an ADF test with a time trend for DOCCSREAL) and, marginally, no unit roots in first-differences, we proceeded to construct models in first-differences. We also tested models in levels.

Assuming the two series have unit roots, we tested to determine if the two series together are cointegrated.[60] We used an Engle-Granger test to determine whether the residuals from a cointegrating regression of the two series are integrated of order 1 (i.e., I(1), a unit root). The resulting tau-statistic from the regression was -1.45, which is well below the Engle-Granger critical value of -3.9 (p-value 0.01) for the null hypothesis that the residual series has a unit root. Therefore, this test did not reject the null hypothesis that the two series, jointly, have a unit root. We concluded that the two series together are I(1) and, therefore, not cointegrated.

Since the two unit root series are not jointly cointegrated, we did not estimate an error correction model. Since there was some ambiguity over the existence of unit roots, we ran a basic regression in both levels and first-differences. The following first-difference results, our preferred approach, were obtained. The sum of the three coefficients total $1,861 per ADP, in 2009 dollars.[61] This point estimate is included as a parameter in the crime model, as shown in Exhibit 9. The three ADP variables are jointly significant with a p-value on the f-test of 0.0042.

[59] Wooldridge (2009): p. 636.
[60] Ibid., p. 639.
[61] We ran this same model with a lagged first difference dependent variable on the right-hand side and the sum of the three coefficients was $2,407. For purposes of our benefit-cost model, which is to compute benefit-cost estimates of evidence-based programs that reduce crime, our preference is to use the non-lagged dependent variable model since it produces a slightly more cautious estimate.

Exhibit 23

Dependent Variable: DOCCSREAL-DOCCSREAL(-1)
Method: Least Squares
Date: 01/19/10 Time: 16:50
Sample (adjusted): 2001 2009
Included observations: 9 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed
bandwidth = 3.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	9209858.	1150172.	8.007374	0.0005
DOCCSADP-DOCCSADP(-1)	1193.120	220.3772	5.413988	0.0029
DOCCSADP(-1)-DOCCSADP(-2)	449.9942	659.9840	0.681826	0.5256
DOCCSADP(-2)-DOCCSADP(-3)	217.7877	483.4093	0.450525	0.6712

R-squared	0.542175	Mean dependent var	8708889.
Adjusted R-squared	0.267480	S.D. dependent var	5067302.
S.E. of regression	4336970.	Akaike info criterion	33.70435
Sum squared resid	9.40E+13	Schwarz criterion	33.79201
Log likelihood	-147.6696	Hannan-Quinn criter.	33.51519
F-statistic	1.973736	Durbin-Watson stat	2.347624
Prob(F-statistic)	0.236419		

This first-difference model is our preferred model. Our model in levels revealed a negative relationship between community supervision average daily population and real expenditures, which does not make intuitive budgeting sense. The first-difference model, shown above, produced the most plausible estimates, given our knowledge of state budget processes.

Victimizations Per-Unit Cost

In addition to costs paid by taxpayers, many of the costs of crime are borne by victims. Some victims lose their lives. Others suffer direct, out-of-pocket personal or property losses. Psychological consequences also occur to crime victims, including feeling less secure in society. The magnitude of victim costs is very difficult—and in some cases impossible—to quantify.

In recent years, however, analysts have taken significant steps in estimating crime victim costs. We use a consistent set of estimates (McCollister, 2010), with some modifications, in WSIPP's benefit-cost model.[62] These crime victim costs build on and modify the previous work prepared for the US Department of Justice by Miller, Cohen, and Wiersema (1996).[63]

These studies divide crime victim costs into two types:

a) *Tangible* victim costs, which include medical and mental health care expenses, property damage and losses, and the reduction in future earnings incurred by crime victims; and

b) *Intangible* victim costs, which place a dollar value on the pain and suffering of crime victims. In these two studies, the intangible victim costs are computed, in part, from jury awards for pain, suffering, and lost quality of life.

The McCollister study divides total tangible costs of crime into tangible victim costs, criminal justice system costs, and crime career costs of offenders (estimates of the economic productivity losses for offenders). In WSIPP's model, we only include McCollister's tangible victim costs since we estimate criminal justice costs separately. We currently do not make estimates of the crime career costs of offenders.

We also use McCollister's intangible victim costs with one exception. McCollister computes a "corrected risk-of-homicide cost" as part of crime-specific intangible victim costs. This is done because, according to McCollister, the FBI's Uniform Crime Reports (UCR) classifies some homicides as other non-homicide crimes when certain offense information is lacking. This FBI reporting practice requires the adjustment made by McCollister. For application to WSIPP's benefit-cost model,

[62] McCollister, K. E., French, M. T., & Fang, H. (2010). The cost of crime to society: New crime-specific estimates for policy and program evaluation. *Drug and Alcohol Dependence, 108*(1), 98-109.
[63] Miller, T. R., Cohen, M. A., & Wiersema, B. (1996). *Victim costs and consequences: A new look* (Document No. NCJ 155282). Washington, DC: National Institute of Justice.

however, this adjustment is not necessary. WSIPP's crime cost estimates are applied to accurately classified conviction data from Washington State; convictions for homicide are not misclassified as other crimes in the Washington system. See section 4.2c of this Chapter for a description of WSIPP's data sources for counting convictions.

WSIPP's model also has one crime category for felony property crimes. The McCollister study breaks property crime classification into motor vehicle theft, household burglary, and larceny/theft. We use these three categories and compute a weighted average property category using the estimated number of crimes calculated for Washington as weights.

WSIPP's modified McCollister crime victim cost estimates are included in the crime model, as shown in Exhibit 9.

Sources of Per-Unit Costs and Uncertainty around Estimates. The bottom portion of Exhibit 9 shows the inputs for source breakouts of criminal justice costs; Washington State inputs and sources are described in Exhibit 24. The input screen in Exhibit 9 also allows the user to input estimated uncertainty around each resource-specific unit cost. This uncertainty is used when Monte-Carlo simulations are run in the model.

Exhibit 24
Proportional of Marginal Criminal Justice Costs by Funding Source

	Operating			Capital		
	State	Local	Federal	State	Local	Federal
Police[1]	15%	85%	0%	22%	78%	0%
Courts & Prosecutors[2]	16%	84%	0%	21%	79%	0%
Juvenile Local Detention	20%[3]	80%	0%	0%[4]	100%	0%
Juvenile Local Supervision	13%[3]	87%	0%	0%[4]	100%	0%
Juvenile State Institution[5]	100%	0%	0%	100%	0%	0%
Juvenile State Supervision[5]	100%	0%	0%	100%	0%	0%
Adult Jail	11%[5]	89%	0%	0%[4]	100%	0%
Adult Local Supervision	27%[5]	73%	0%	0%[4]	100%	0%
Adult State Prison[6]	100%	0%	0%	100%	0%	0%
Adult Post Prison Supervision[6]	100%	0%	0%	100%	0%	0%

[1] Justice Expenditure and Employment Extracts, 2010 - Preliminary, Tracey Kyckelhahn, Ph.D., Tara Martin, BJS Intern, July 1, 2013. NCJ 242544, Table 4: Justice system expenditure by character, state and type of government, fiscal 2010, available at: http://www.bjs.gov/index.cfm?ty=pbdetail&iid=4679. Direct current Police Protection expenditures for state and local governments for Washington State.
[2] Justice Expenditure and Employment Extracts, 2010 - Preliminary, Tracey Kyckelhahn, Ph.D., Tara Martin, BJS Intern, July 1, 2013. NCJ 242544, Table 4: Justice system expenditure by character, state and type of government, fiscal 2010, available at: http://www.bjs.gov/index.cfm?ty=pbdetail&iid=4679. Direct current Judicial and Legal expenditures for state and local governments for Washington State.
[3] Sources for operating costs of juvenile local detention and juvenile local supervision estimated by analyzing information from the Washington State Auditor's Local Government Finance Reporting System (LGFRS) system. (Functional Group/BARS Summary, Expenditures for government types City/Town and County, All Objects, All Available Fund Types, for 2011). http://portal.sao.wa.gov/LGCS/Reports/, Juvenile Services (BARS account: 527).
[4] WSIPP assumes capital costs for all local juvenile and adult resources are 100% locally funded.
[5] Sources for operating costs of adult jail and adult local supervision estimated by analyzing information from the Washngton State Auditor's Local Government Finance Reporting System (LGFRS) system. (Functional Group/BARS Summary, Expenditures for government types City/Town and County, All Objects, All Available Fund Types, For 2011). http://portal.sao.wa.gov/LGCS/Reports/, Detention and Correction (BARS account: 523).
[6] WSIPP assumes all state funded.

Not all crime is reported to, or acted upon by, the criminal justice system. When crimes are reported by citizens or detected by police or other officials, however, the use of taxpayer-financed resources begins. The degree to which these resources are used depends on the crime as well as the policies and practices governing the criminal justice system's response. In the preceding section, we describe the *per-unit* marginal cost estimates used in our model. In this section, we discuss *how many units* of the criminal justice system are used when a crime occurs.

Once a person is convicted for a criminal offense, sentencing policies and practices in Washington affect the use of different local and state criminal justice resources. Exhibit 25 is a screen shot from WSIPP's benefit-cost model that displays how criminal justice resources in Washington State are used in response to crime. The estimates for each row in Exhibit 25 are described below.

Probability of Resource Use. The first block of information in Exhibit 25 displays parameters indicating the probability that a person convicted for one of the seven crime categories modeled will receive a sentence to a juvenile state institution (instead of local juvenile detention) or adult state prison (instead of local adult jail). For example, if an adult offender is convicted of robbery, there is a 71% chance the offender will receive a prison sentence and a 29% chance of receiving a jail sentence. These sentencing probabilities were obtained from the Washington State Sentencing Guidelines Commission.[64]

Number of Years of Use per Resource. We estimate the average number of years various criminal justice resources are used for each of the crime categories.

Juvenile Detention (with local or state sentence). Unfortunately, Washington does not have an annual reporting system on local juvenile detention length of stay. Therefore, the average length of stay at local juvenile detention facilities and the average length of local probation were estimated from an earlier survey of juvenile courts conducted by WSIPP.[65]

Juvenile Local Supervision. The average length of stay on probation was also estimated from the same survey of juvenile courts conducted by WSIPP.[66]

Juvenile State Institution. The average length of stay in a juvenile state institution was estimated using data obtained from the Sentencing Guidelines Commission.[67]

Juvenile State Supervision. The average length of stay on juvenile parole was estimated using information obtained from the Juvenile Rehabilitation Administration.[68]

Adult Jail, With Local Sentence. The average length of stay in jail for local sentences was estimated using data from the Sentencing Guidelines Commission.[69]

Adult Jail, With Prison Sentence. Analysis from the Department of Corrections on the credit for time served in jail was used to estimate the total length of stay in jail prior to prison.[70]

Adult Community Supervision and Adult Post Prison Supervision. These numbers were obtained from the Sentencing Guidelines Commission.[71]

Adult Prison. The information for the average sentence received for adults sentenced to a state prison comes from Sentencing Guidelines Commission data. As a result of good-time reductions to some prison sentences, the average time actually served is often shorter than the original sentence. Exhibit 25 shows the average prison length of stay, which is computed in the model by multiplying the sentence length of stay by an average percentage good-time reduction. The data on the average sentence reductions, by crime, were obtained from an analysis supplied by the Washington State Department of Corrections.

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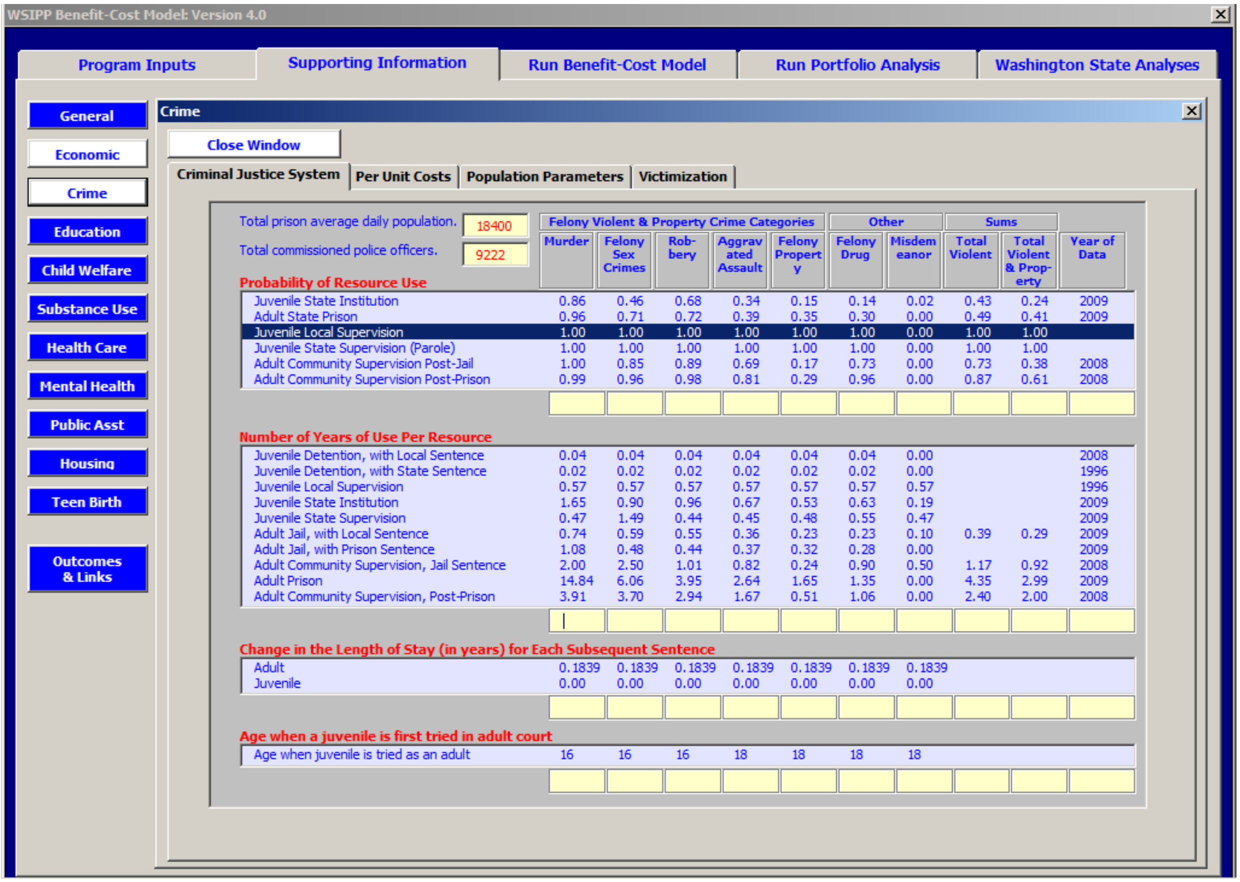
[64] Juvenile sentencing information obtained from SGC staff via email on March 10, 2010. Adult sentencing information obtained from: Sentencing Guidelines Commission. (2009, January). *Statistical summary of adult felony sentencing: Fiscal year 2008*. Olympia, WA: Author, Table 1.
[65] Burley & Barnoski (1997).
[66] Ibid.
[67] Washington State Sentencing Guidelines Commission (personal communication, March 10, 2010).
[68] Washington State Juvenile Rehabilitation Administration (personal communication, April 18, 1997).
[69] Sentencing Guidelines Commission (2009): Table 1.
[70] Washington State Department of Corrections (personal communication, November 7, 1996).
[71] Washington State Sentencing Guidelines Commission (personal communication, April 6, 2010).

Exhibit 25



	Felony Violent & Property Crime Categories					Other		Sums		
	Murder	Felony Sex Crimes	Rob-bery	Aggravated Assault	Felony Property	Felony Drug	Misdemeanor	Total Violent	Total Violent & Property	Year of Data
Probability of Resource Use										
Juvenile State Institution	0.86	0.46	0.68	0.34	0.15	0.14	0.02	0.43	0.24	2009
Adult State Prison	0.96	0.71	0.72	0.39	0.35	0.30	0.00	0.49	0.41	2009
Juvenile Local Supervision	1.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00	1.00	
Juvenile State Supervision (Parole)	1.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00	1.00	
Adult Community Supervision Post-Jail	1.00	0.85	0.89	0.69	0.17	0.73	0.00	0.73	0.38	2008
Adult Community Supervision Post-Prison	0.99	0.96	0.98	0.81	0.29	0.96	0.00	0.87	0.61	2008
Number of Years of Use Per Resource										
Juvenile Detention, with Local Sentence	0.04	0.04	0.04	0.04	0.04	0.04	0.00			2008
Juvenile Detention, with State Sentence	0.02	0.02	0.02	0.02	0.02	0.02	0.00			1996
Juvenile Local Supervision	0.57	0.57	0.57	0.57	0.57	0.57	0.57			1996
Juvenile State Institution	1.65	0.90	0.96	0.67	0.53	0.63	0.19			2009
Juvenile State Supervision	0.47	1.49	0.44	0.45	0.48	0.55	0.47			2009
Adult Jail, with Local Sentence	0.74	0.59	0.55	0.36	0.23	0.23	0.10	0.39	0.29	2009
Adult Jail, with Prison Sentence	1.08	0.48	0.44	0.37	0.32	0.28	0.00			2009
Adult Community Supervision, Jail Sentence	2.00	2.50	1.01	0.82	0.24	0.90	0.50	1.17	0.92	2008
Adult Prison	14.84	6.06	3.95	2.64	1.65	1.35	0.00	4.35	2.99	2009
Adult Community Supervision, Post-Prison	3.91	3.70	2.94	1.67	0.51	1.06	0.00	2.40	2.00	2008
Change in the Length of Stay (in years) for Each Subsequent Sentence										
Adult	0.1839	0.1839	0.1839	0.1839	0.1839	0.1839	0.1839			
Juvenile	0.00	0.00	0.00	0.00	0.00	0.00	0.00			
Age when a juvenile is first tried in adult court										
Age when juvenile is tried as an adult	16	16	16	18	18	18	18			

Change in the Length of Stay for Each Subsequent Sentence. In Washington, the sentence for a crime is based on the seriousness of the offense and the offender's criminal history. The Sentencing Guidelines Commission (SGC) publishes a grid showing the sentence by seriousness and the number of previous convictions. The sentence length for a given crime increases as criminal history increases. The amount of time actually served is often shorter than the original sentence. Exhibit 25 shows the average prison length of stay, which is computed in the model by multiplying the sentence length of stay by an average percentage good-time reduction. The data on the average sentence reductions, buy crime, were obtained from an analysis supplied by the Washington State Department of Corrections.

To account for these lengthening sentences, we use the sentencing grid and WSIPP's average length of stay data to create a new sentencing grid weighted for the frequency of conviction and the likelihood of prison. This enables us to estimate the effect of increasing trips through the criminal justice system on sentence length.

We estimate this first by determining the average length of stay for recidivists convicted of the following offense categories: murder, sex, robbery, assault, property, drug, and misdemeanor. We assume offenders who are released from prison have at least three prior offenses and then determine the following:

- likelihood of conviction;
- likelihood of going to prison if convicted; and
- average length of stay (LOS).

Next, we determine what the offense seriousness level is upon the fourth conviction. We do this by matching the length of stay for the offense category with the seriousness level in the sentencing grid and with a sentence most similar to the length of stay. For example, the average length of stay in prison for murder (all offenses from manslaughter through first degree murder) is displayed in the input screen above. This length of stay, with three prior offenses, is closest to the sentence at Seriousness Level XIII.

We then weight the sentences in the grid for the likelihood of recidivism in the offense categories and the likelihood of going to prison.

Finally, we create a single grid with increased average sentences by increased number of prior convictions. We plot this weighted average sentence by number of offenses. The result is a linear relationship; the slope indicates that each subsequent conviction increases the average prison sentence by an additional portion of a year. As of the date of this publication, we have not computed a similar procedure for juvenile repeat offenders sentenced to state institutions.

Age When a Juvenile Is First Tried in Adult Court. Under Washington's current laws, the age at which a youth is considered an adult varies for specific types of crimes. Exhibit 25 contains information on the maximum age for juvenile court jurisdiction by type of crime. The actual determination of juvenile or adult court jurisdiction depends on several factors, in addition to a person's age and his or her crime. The model uses the information in Exhibit 25 as representative of the typical decisions made pursuant to current Washington State law.

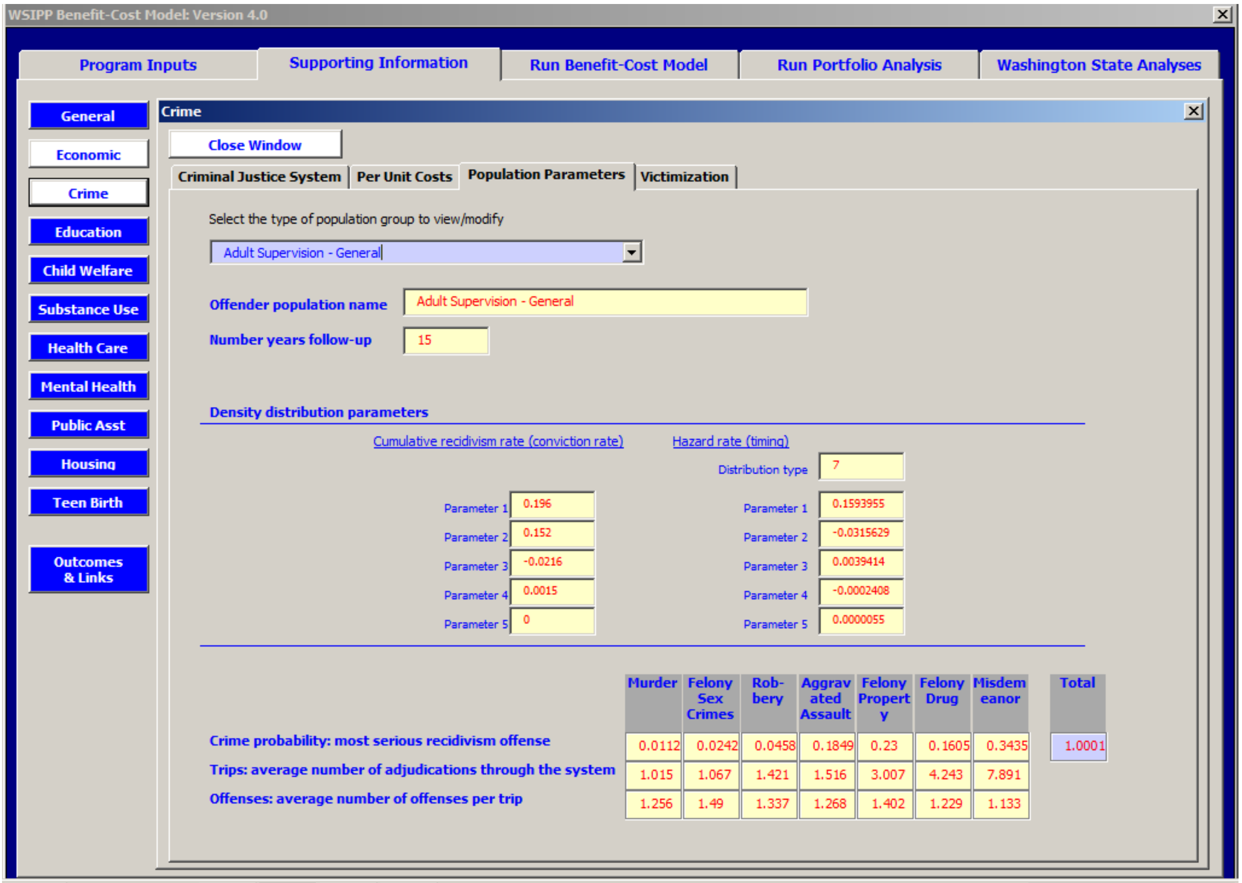
4.2b Criminological Information for Different Populations

To estimate the long-run impacts of evidence-based programs on crime, WSIPP combines program effect sizes with crime information from various populations in Washington State. To do this analysis, we calculate 15-year recidivism trends for an offender cohort; for non-offender populations, we calculate the probability of obtaining a conviction over the life-course (35 years).

Crime Parameters. As shown in Exhibit 26, we calculate the following information for each of the offender and non-offender populations:

- Conviction Rate. We estimate the cumulative conviction rate for felony and misdemeanor crime in Washington over the 15-year follow-up period. We compute the cumulative conviction rate using a fourth-order polynomial density distribution. These conviction rates, by year, are used to calculate the unit change in crime as described in section 4.2 of this Chapter.
- Crime Probability. For people who do commit crimes during the follow-up period, we calculate the probability of being convicted for a certain type of crime using a ranked order of seriousness. The mutually exclusive categories from most serious to least serious include murder, sex, robbery, assault, property, drug, and misdemeanor.
- Trips through the System. We calculate the total number of adjudications, defined as the number of "trips" through the criminal justice system, during the follow-up period. We also determine the average number of trips per offender during the follow-up period.
- Volume of Offenses. It is possible for offenders to have multiple offense convictions for each trip through the system. Thus, we also calculate the total number of offenses during the follow-up period, as well as the average number of offenses per adjudication. Adjudications and offenses are broken into murder, sex, robbery, assault, property, drug, and misdemeanor.
- Timing. For those persons convicted, we compute a probability density distribution for each of the offender and non-offender populations using exponential, lognormal, polynomial (second-order), or power distributions, which indicate when convictions are likely to happen over the follow-up period.

Exhibit 26



Offender Populations. Recidivism is defined as any offense committed after release to the community, or after initial placement in the community, that results in a conviction in Washington State from adult or juvenile court.[72] In addition to the 15-year follow-up period, a one-year adjudication period is added to allow for court processing of any offenses that occur at the end of the follow-up period. Crime parameters are calculated using WSIPP's criminal history database, which is a synthesis of information for offenders convicted in Washington State.[73]

We collected recidivism data on five general offender populations who became "at-risk" for recidivism in the community during calendar year 1993. For adult offenders, we observe recidivism patterns for (1) offenders released from Department of Corrections' (DOC) facilities and (2) offenders sentenced directly to DOC community supervision. For juvenile offenders, we observe recidivism patterns for (3) youth released from Juvenile Rehabilitation Administration (JRA) facilities, (4) youth sentenced to diversion through local-sanctioning courts, and (5) youth sentenced to detention/probation through local-sanctioning courts. We calculated separate crime distributions for each offender population.

We further break down the general offender populations into risk for reoffense categories. Risk for reoffense is calculated using criminal history data to determine offenders' probability of future reoffense, and grouped into low, moderate, and high risk categories.[74] Additionally, we created and analyzed adult and juvenile sex offender populations based on the most serious current offense of conviction prior to the 15-year follow-up period.

[72] Barnoski, R. (1997). *Standards for improving research effectiveness in adult and juvenile justice. (*Document No. 97-12-1201). Olympia: Washington State Institute for Public Policy, p. 2.
[73] Criminal history data are from the Washington State Administrative Office of the Courts and Department of Corrections.
[74] See Barnoski R. & Drake, E. (2007). *Washington's offender accountability act: Department of Corrections' static risk instrument* [Revised October, 2008] (Document No. 07-03-1201). Olympia: Washington State Institute for Public Policy. See also, Barnoski, R. (2004). *Assessing risk for re-offense: Validating the Washington State juvenile court assessment.* (Document No. 04-03-1201). Olympia: Washington State Institute for Public Policy.

Non-Offender Population. To determine the impact of prevention programs on future crime, we calculate the probability of obtaining a conviction over the life-course for a birth cohort. We select felony and misdemeanor offenders from WSIPP's criminal history database who were born in 1974 (n=78,517) to determine how many people were convicted at age 8, age 9, age 10, and so on. The 1974 birth cohort gives us the longest follow-up period (36 years) possible using Washington State criminal records data. Using Office of Financial Management state population data, we abstract the number of people living in Washington State, and born in 1974, for each of the follow-up years. For example, in 1994, there were 66,709 20-year-olds (1974 birth cohort) living in Washington. We estimate the average size of the 1974 cohort each follow-up year weighted by crime propensity. Future crime probability is adjusted as the life-course progresses.

Low-Income Non-Offender Population. We also estimate criminological information for a low income population by adjusting the non-offender population described above using poverty and arrest data from the National Survey on Drug Use and Health.[75] Specifically, we estimate for the low-income population (1) a new base conviction rate over the life-course and (2) the probability of being convicted for a certain crime.

To do this, we use multivariate logistic regression analysis to determine the effect of poverty on crime with arrests as the dependent variable and poverty as the independent variable along with relevant control variables (See Exhibit 27). Poverty is measured as less than 200% of the federal poverty threshold. The coefficient from this model indicates that poverty is significantly related with a greater likelihood of crime (b=.803, p<.0001). We use the coefficient to adjust the base conviction rate over the life-course by calculating the odds ratio multiplied by the base conviction rate at any year over the life-course, divided by the odds ratio of the base conviction rate remaining over the life-course (for example, exp(0.803))0.33)/((1-0.33) +0.33(exp0.803)).

We adjust the probability of being convicted for a certain type of crime by conducting individual multivariate regression analyses for arrests for a violent crime, arrests for a property crime, arrests for a drug crime, and arrests for other crime. We take the ratio of the odds ratios for each of those crime categories relative to the total poverty effect and multiple the ratio of odds ratios by the crime probability for the non-offender population and normalize the crime probability to one.

Exhibit 27

	Type of Arrest				
	Any	**Violent**	**Property**	**Drug**	**Other**
Intercept	-4.717	-6.457	-7.024	-7.062	-5.111
Poverty	0.803	1.013	1.126	0.630	0.653
Male	1.148	1.213	0.726	1.039	1.196
Age 12-13	-1.095	-0.269	0.623	0.038	-2.160
Age 14-15	0.157	0.734	1.606	0.769	-0.667
Age 16-17	0.598	0.850	1.847	1.525	-0.160
Age 18-20	1.058	0.864	1.904	1.827	0.700
Age 21-25	0.978	0.772	1.277	1.908	0.733
Age 26-34	0.676	0.645	1.498	0.880	0.517
Black	0.462	0.653	0.286	0.512	0.321
Native American	1.008	1.613	-0.168	0.601	0.815
Pacific Islander	0.161	-0.253	-0.666	-0.444	0.443
Asian	-1.615	-3.029	-2.317	-1.766	-1.235
Hispanic	0.052	0.299	-0.202	-0.496	0.094
Married	-1.019	-1.172	-1.027	-1.291	-0.990
Model Fit	0.750	0.752	0.734	0.778	0.746

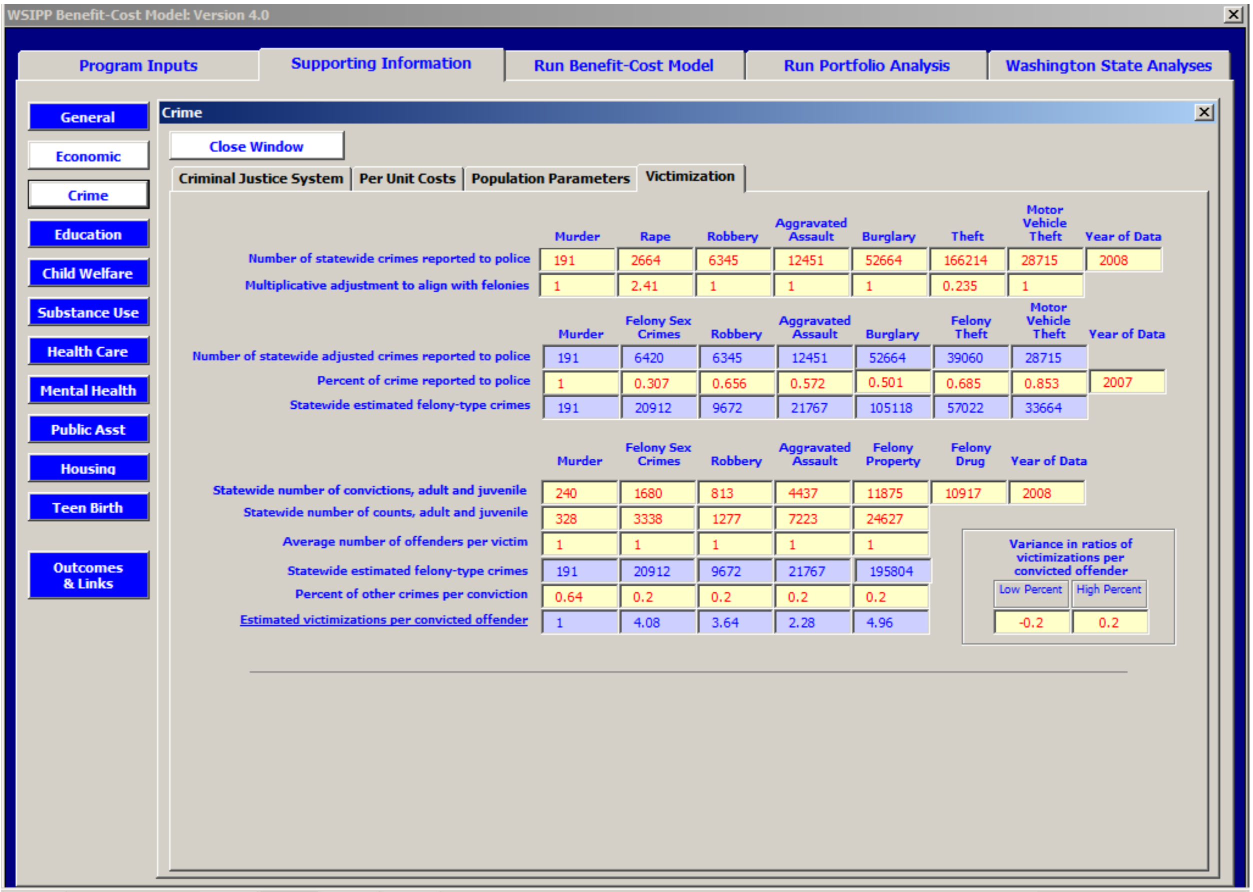
All variables were statistically significant for all models at p<.001.

[75] U. S. Department of Health and Human Services, Substance Abuse and Mental Health Services Administration, Office of Applied Studies. (2010, November 16). *National Survey on Drug Use and Health, 2009* [Computer file]. ICPSR29621-v1. Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor]. doi:10.3886/ICPSR29621.

4.2c Estimates of Victimizations per Conviction

Nearly all of the effect sizes computed from programs and policies impacting crime describe official measures of criminal activity, such as convictions or arrests. There may be, of course, many more criminal victimizations than those reported in official measures of crime. To estimate the number of victimizations per officially reported crime, WSIPP's benefit-cost model uses additional information. Exhibit 28 is a screen shot that displays the information. Yellow boxes contain inputs entered by the user while blue boxes contain calculated results. Inputs in Exhibit 28 are described below.

Exhibit 28



	Murder	Rape	Robbery	Aggravated Assault	Burglary	Theft	Motor Vehicle Theft	Year of Data
Number of statewide crimes reported to police	191	2664	6345	12451	52664	166214	28715	2008
Multiplicative adjustment to align with felonies	1	2.41	1	1	1	0.235	1	

	Murder	Felony Sex Crimes	Robbery	Aggravated Assault	Burglary	Felony Theft	Motor Vehicle Theft	Year of Data
Number of statewide adjusted crimes reported to police	191	6420	6345	12451	52664	39060	28715	
Percent of crime reported to police	1	0.307	0.656	0.572	0.501	0.685	0.853	2007
Statewide estimated felony-type crimes	191	20912	9672	21767	105118	57022	33664	

	Murder	Felony Sex Crimes	Robbery	Aggravated Assault	Felony Property	Felony Drug	Year of Data
Statewide number of convictions, adult and juvenile	240	1680	813	4437	11875	10917	2008
Statewide number of counts, adult and juvenile	328	3338	1277	7223	24627		
Average number of offenders per victim	1	1	1	1	1		
Statewide estimated felony-type crimes	191	20912	9672	21767	195804		
Percent of other crimes per conviction	0.64	0.2	0.2	0.2	0.2		
Estimated victimizations per convicted offender	1	4.08	3.64	2.28	4.96		

Variance in ratios of victimizations per convicted offender	
Low Percent	High Percent
-0.2	0.2

Number of statewide crimes reported to the police. Uniform Crime Report (UCR) data for all policing agencies are obtained from the Washington Association of Sheriffs and Police Chiefs. We adjust the data to account for non-reporting agencies. The data are then aggregated to statewide annual data.

Multiplicative adjustment to align UCR data with Washington felonies. Two of the UCR-reported crime categories, rape and felony theft, do not align with felony conviction data as defined by the Revised Code of Washington. Thus, we apply a multiplicative adjustment factor to align reported crimes with felony convictions.

Rape, as defined by the UCR, does not include other sexual assaults, sexual offenses with male victims, or victims under the age of 12. We adjust UCR reported rapes using National Crime Victimization Survey data to estimate male victims[76] and other sexual assaults.[77] Data from the National Incident Based Reporting System are used to adjust for the percentage of all sex offenses where victims are under age 12.[78]

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[76] Bureau of Justice Statistics. (2008). *Criminal victimization in the United States, 2006 statistical tables: National crime victimization survey* (Document No. NCJ 223436), Washington, DC: United States Department of Justice, Author, Table 2.

[77] Ibid., Table 1.

[78] Snyder, H. N. (2000). *Sexual assault of young children as reported to law enforcement: Victim, incident, and offender characteristics* (Document No. NCJ 182990). Washington, DC: United States Department of Justice, Bureau of Justice Statistics.

Theft is adjusted to include only thefts valued at $750 or more, the cutoff for a felony theft, as defined by the Revised Code of Washington. We use National Crime Victimization Survey data of thefts reported to the police to estimate this figure.[79]

Percentage of crimes reported to the police. We adjust our victimization estimates to include crimes not reported to the police using reporting rate data obtained from the National Crime Victimization Survey.[80] We adjust the percentage of crimes reported to police from the NCVS for sex offenses and theft offenses to reflect the multiplicative adjustment to align UCR data with Washington felonies.

Statewide number of convictions, adult and juvenile. Adult and juvenile felony conviction data are obtained from the Administrative Office of the Courts.[81]

Average number of offenders per victim. Many victimizations are committed by groups of offenders, thus we estimate the average number of offenders per victimization using data from the National Incident Based Reporting System (NIBRS).[82] We use the offender sequence number in the NIBRS data, which indicates the number of offenders for each incident, and we determine the average number of offenders for each broad offense category.

Percentage of other crimes per conviction. To estimate the total number of crimes per convicted offender, we apply a multiplicative factor to adjust for the likely possibility that there are multiple victimizations per conviction. To our knowledge, no research exists to date that indicates the appropriate value. Thus, we simply apply an estimate of 20%. A value of zero would imply one victimization per conviction, while a value of one would imply all crimes are attributed to those offenders convicted.

Variance in ratios of victimizations per convicted offender. Since the previous parameter, the percentage of other crimes per conviction, is estimated with considerable imprecision, in Monte Carlo simulation the parameter is selected from a triangular probability distribution that bounds risk. The user can enter a low and high percentage that is then applied to the parameter. We have chosen 20 percent lower and 20 percent higher bounds for the triangular distribution.

4.2d Procedures to Estimate Criminal Justice System and Victimization Events

In this section of the Benefit-Cost Technical Manual, we describe how the inputs from the previous sections are used to calculate victimizations and costs avoided. In some instances, we also count the quantity of criminal justice events, such as prison beds, avoided.

Criminal Justice System Resources.

For each criminal justice resource, as seen in Exhibit 9, we estimate costs avoided using the following equation:

$$(4.7)\quad CjsResource\$_{ry} = \sum_{c=1}^{C} \sum_{t=1}^{ceiling(T_c)} \sum_{f=1}^{F} \left[CjsEvent_{yctf} \times CrimePr_c \times CjsResourcePrW_{rc} \times TripPr_{ct} \times TimetoRecid_f \times Unit\Delta_y \times CjsResourceCost_{rc} \right] \times RecidRate$$

We also count Average Daily Population prison beds avoided. We do this using equation 4.7 above however; we do not multiply by the $CjsResourceCost_{rc}$.

Variable Definitions*.* Below are definitions and calculations for the variables used in equation 4.7.

C—The number of crime types modeled, ranked from most serious crime category to least serious. For example, we use seven crime types ranked in the following order: murder, sex offenses, robbery, aggravated assault, property, drug, and misdemeanors.

F—The number of years in the recidivism follow-up.

Y—The at-risk year following treatment.

[79] Bureau of Justice Statistics (2008): Table 100.
[80] Ibid.
[81] Washington State Administrative Office of the Courts, Superior Court Annual Tables, available from http://www.courts.wa.gov/caseload/?fa=caseload.showIndex&level=s&freq=a
[82] U. S. Department of Justice. Federal Bureau of Investigation. *National incident-based reporting system, 2008* [Computer file]. ICPSR27647-v1. Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor], 2010-05-03. doi:10.3886/ICPSR27647.

T—The number of trips (adjudications) through the system rounded up. For example, prison offenders, whose most serious reoffense is a sex offense, have an average number of 1.08 trips in a 15-year follow-up period. Thus, the total possible number of trips through the system is two with the probability of the second trip being less than 0.08. See also $TripPr_{ct}$.

$CjsEvent_{yctf}$ —Variable indicating if and when a criminal justice resource is used and, if so, how much of the resource is used during the at-risk year. Criminal justice resources are shown in Exhibit 9. The Visual Basic Programming language for $CjsEvent_{yctf}$ is shown in Exhibit 28.

$CrimePr_c$ —Among those who re-offend, the probability that the most serious offense occurring during the follow-up period is of type *c*. The data for populations are show in Exhibit 26.

$CjsResourcePrW_{rc}$.—The probability that a criminal justice resource, *r*, will be used for a specific type of crime, *c*. See Exhibit 25. For example, not all offenders who are convicted of a crime will necessarily receive a prison sentence. The $CjsResourcePrW_{rc}$ for police and courts is one.

$TripPr_{ct}$—The probability that a trip, a criminal justice event resulting in an adjudication during the follow-up period, occurs for crime c for trip t as show in Exhibit 26. The probability of a trip occurring is one. Once a whole trip has been used, then we use the remaining probability of the trip. For example, prison offenders whose most serious reoffense is a sex offense have an average number of 1.08 trips in a 15-year follow-up period. Thus, there is a probability of one trip occurring and a probability of 0.08 remaining trips.

$TripSpaces_c$—The number of years in the follow-up period divided by the number of $Trips_c$. This estimate enables us to distribute the total number of adjudications over the 15-year period.

$TimetoRecid_f$—Among those who re-offend during the recidivism follow-up period *f*, the probability that the recidivism event happens in year *f*. The sum of $TimetoRecid_f$ = 1.0.

$Unit\Delta_y$ —The change in the probability of being an offender (vs. not being an offender) in year y.

$CjsResourceCost_{rc}$—The per unit marginal costs of each criminal justice resource as estimated in section 4.2a of this Chapter and as shown in Exhibit 9.

RecidRate—The percentage of offenders who have a Washington State court legal action during the recidivism follow-up period F for that specific offender population as shown in Exhibit 26. Different recidivism base rates are used depending on the specific population that receives a given program. See Exhibit 26.

Exhibit 29

Visual Basic Programming Code Used to Calculate *CjsEvent*$_{yctf}$

```
RowCount = 0
  For c = 1 To CrimeTypes
    For t = 1 To TripsCeiling(c, 1)
      If t <= Trips(c, 1) Then
      TripMultiplier = 1
      Else
      TripMultiplier = Trips(c, 1) - Int(Trips(c, 1))
      End If
      AgeTemp = age + (t - 1) * TripSpaces(c, 1)

      For f = 1 To FollowUpYears
        RowCount = RowCount + 1
        If AgeTemp < AgeofAdultCJS(c, 1) Then GoTo SkipAdult

        For y = 1 To MaxAtRiskYears
          If (f + ((t - 1) * TripSpaces(c, 1))) > y Then
                CjsEvent(RowCount, y) = 0
          ElseIf y > f And CjsEvent(RowCount, y - 1) = 0 Then
                CjsEvent (RowCount, y) = 0
          ElseIf Int(CjsResourceLength) + (f + ((t - 1) * TripSpaces(c, 1))) = y Then
                 CjsEvent(RowCount, y) = CjsResourceLength - Int(CjsResourceLength)
          ElseIf y > CjsResourceLength + (f + ((t - 1) * TripSpaces(c, 1))) Then
                CjsEvent(RowCount, y) = 0
          Else
                CjsEvent(RowCount, y) = 1
          End If

          CjsResourceAvoided(1, y) = CjsResourceAvoided (1, y) _
            + CjsEvent(RowCount, y) _
            * CrimeProbCjs(c, 1) _
            * CjsResourceProb(c, 1) _
            * TimeToRecid(f, 1) _
            * TripMultiplier _
            * UnitChange(f, 1)
        Next y
SkipAdult:
   AgeTemp = AgeTemp + 1
      Next f
    Next t
  Next c
  For y = 1 To MaxAtRiskYears
    CjsResourceAvoided (y, 1) = CjsResourceAvoidedSum(1, y)
  Next y
```

Victimizations Avoided

Using information from Exhibit 26, we estimate the number of victimizations avoided and victimization costs avoided using the following equation:

$$(4.8)\quad Victim\$_{ry} = \sum_{c=1}^{C}\ \sum_{t=1}^{ceiling(Trips_c)}\ \sum_{f=1}^{F}\left[VictimEvent_{yctf} \times VictimVolume_{yctf} \times CrimePr_c \times TripPr_{ct} \times_f Unit\Delta_y \times VictimCost_{rc}\right] \times RecidRate$$

Variable Definitions. Below are definitions and calculations for the variables used in equation 4.8 unless otherwise defined in the aforementioned section, criminal justice system resource variable definitions.

VictimVolume$_{ctf}$. The volume of victimizations is estimated using a three-step process. First, we estimate the number of victimizations avoided for the most serious offense in the follow-up period. Second, since there are usually other offenses adjudicated at the time of the most serious offense, we calculate the additional offenses and related victimizations. Finally, we calculate the number of victimizations avoided for the trips through the criminal justice system during the remainder of the follow-up period.

F – The number of years in the recidivism follow-up time trips ceiling for that offense type. For example, prison offenders whose most serious reoffense is a sex offense have an average number of 1.08 trips in a 15-year follow-up period. Thus, the ceiling of the total number of trips that need to be modeled are two.

$$(4.9)\quad VictimVolume_{cf} = \sum_{c=1}^{C}\sum_{v=c}^{C}\sum_{f=1}^{F}\frac{(MostSeriousTripVic_c + AddVicsMostSeriousTrip_c + RemainingTrips_c)}{Trips_c}$$

Equations 4.10, 4.11, and 4.12 show our calculations for each component of $VictimVolume_{yctf}$. In the following equations, when c equals v, we estimate the most serious offense using the following formulas. Otherwise, c, the most serious crime, is equal to zero.

$$(4.10)\quad MostSeriousTripVic_c = 1 \times VicsPerConvictedOffender$$

$$(4.11)\quad AddVicsMostSeriousTrip_c = OffensesPerTrip_c \times VicsPerConvictedOffender_v \times \left(\frac{CrimePr_v}{\sum_{c=1}^{C} CrimePr_c}\right)$$

$$(4.12)\quad RemainingTrips_c = (Trips_c - 1) \times OffensesPerTrip_c \times VicsPerConvictedOffender_c \times \left(\frac{CrimePr_v}{\sum_{c=1}^{C} CrimePr_c}\right)$$

$VictimEvent_{yctf}$. A dichotomous variable indicating if a victimization event has occurred during the at-risk year. Victimizations are shown in Exhibit 28. The Visual Basic Programming language for *VictimEventyctf* is shown in Exhibit 30.

VictimCostrc. The per unit cost of crime to victims as estimated in section 4.2 of this Chapter and as shown in Exhibit 9.

Exhibit 30

Visual Basic Programming Code Used to Calculate *VictimEvent*$_{yctf}$.

```
For v = 1 To CrimeTypes
RowCount = 0
    For c = 1 To CrimeTypes
      For t = 1 To TripsCeiling(c, 1)
        If t <= Trips(c, 1) Then
          TripMultiplier = 1
        Else
          TripMultiplier = Trips(c, 1) - Int(Trips(c, 1))
        End If
        For f = 1 To FollowUpYears
          RowCount = RowCount + 1
            For y = 1 To MaxAtRiskYears
              If y > f then
                VictimEvent(RowCount, y) = 0
              ElseIf f + (t - 1) * TripSpaces(c, 1) = y Then
                VictimEvent(RowCount, y) = 1
              Else
                VictimEvent (RowCount, y) = 0
              End If
             AvoidedVictims(v, y) = AvoidedVictims(v, y) _
                + VictimEvent (RowCount, y) _
                * CrimeProbCjs(c, 1) _
                * TimeToRecid(f, 1) _
                * TripMultiplier _
                * UnitChange(f, 1) _
                * VictimVolume(RowCount, v)
            Next y
        Next f
      Next t
    Next c
Next v
```

4.2e Linkages: Crime and Other Outcomes

WSIPP's benefit-cost model monetizes improvements in crime, in part, with linkages between crime and other outcomes to which a monetary value can be estimated. The parameters for these linkages are obtained by a meta-analytic review of relevant research literature. For example, we estimate the relationship between juvenile crime and high school graduation by meta-analyzing the most credible studies that have addressed this topic. The meta-analytic process provides both an expected value effect given the weight of the evidence and an estimate of the error of the estimated effect. Both of these parameters are entered into the benefit-cost model and used when performing a Monte Carlo simulation. The linkages in the current WSIPP model are listed in Chapter 5.

4.2f Special Calculations for Prison and Policing Resources

As noted in Chapter 2.2, two crime topics that estimated with a different effect size metric than the other topics described in this Technical Manual. The two topics are how prison incarceration rates affect crime and how the number of police officers affects crime. These two literatures are most often summarized with an "elasticity" effect size metric, rather than a D-cox or Cohen's d effect size metric. This section of the technical manual describes the particular methods we use to estimate effects and monetize outcomes for these two elasticity-based topics. The input screen displayed below shows some of the parameters for these calculations.

Our first analytical task is to conduct a meta-analytic review of the research literature from the United States and beyond to determine if prison and police are effective at reducing crime rates. We examine studies that have measured how prison average daily population (ADP) or the number of police officers (POL) affect current crime rates. WSIPP's meta-analytic results for these two topics are described in a separate WSIPP report.[83]

[83] The November 2013 WSIPP report on prison and policing, available at: http://www.wsipp.wa.gov/rptfiles/13-11-1901.pdf

There is a research literature on the effect of incarceration rates on crime.[84] Many of the studies addressing this relationship in the United States construct models using state-level data over a number of years to estimate the parameters of an equation of this general form:

$$(4.13)\quad C_{tsy} = a + b(ADP_{sy}) + c(X_{sy}) + e$$

In this typical model, crime, C, of type, t, in state, s, and year, y, is estimated to be a function of a state's overall average daily prison population, ADP, a vector of control variables, X, often including state and year fixed effects, and an error term, e. Some studies use this type of model to estimate total reported crime, while others examine types of crime such as violent crime or property crime.

There is similar research literature on the effect of the number of police officers on crime rates.[85] Many of these studies use data at the city or county level to estimate the parameters of an equation of this form:

$$(4.14)\quad C_{tcy} = a + b(POL_{cy}) + c(X_{cy}) + e$$

In a typical police model, crime, C, of type, t, in city or county, c, and year, y, is estimated to be a function of the size of a city's or county's overall commissioned police force, *POL*, a vector of control variables, X, often including city/county and year fixed effects, and an error term, e.

In the research literature we reviewed, these models are almost always estimated with a log-log functional form, at least for the dependent and policy variables. Several authors have observed that the panel time series often used to estimate equations 4.13 and 4.14 are likely have unit roots, especially with state level data.[86] Thus, to help avoid estimating spurious relationships, some authors estimate equations 4.13 and 4.14 in first-differences since the time series typically do not exhibit unit roots after differencing once.

As noted later, there is considerable concern in the research literature on the econometric implications of possible simultaneous relationships between the variables of interest in equations 4.13 and 4.14 and in omitted variables bias.[87] Simultaneity can occur because crime may be a function of ADP or POL, but ADP and POL may also be a function of crime. Failure to account for these simultaneous relationships, as well as failure to address omitted control variables in regressions, can cause statistically biased estimates. In recent years, much of the discussion and debate in the research literature has focused ways to address statistical bias from simultaneity and omitted control variables.

The dependent variable: crime. In the American studies estimating equations 4.13 and 4.14, crime is most often measured with data from the Federal Bureau of Investigation's Uniform Crime Reports (UCR). These data count the number of crimes reported to police. Some studies estimate a model of total UCR crime reported to police, while other studies estimate two equations, one for violent crime reported to police, and another for property crime reported to police. Still other studies break the analysis down further and estimate equations for the seven major types of "Part 1" crimes in the UCR data: murder, rape, robbery, aggravated assault, burglary, theft, and motor vehicle theft. These data are entered by the user on the input screen shown in Exhibit 28.

Most studies in our review also recognize that not all crimes are reported to police. Accordingly, most authors, in drawing conclusions from their analyses, use information from the annual National Crime Victimization Survey (NCVS) to obtain estimates about how often crime victims say they report crimes to police.[88] Reporting rates are then used to adjust the coefficients estimated with equations 4.13 and 4.14 to produce estimates on how the total amount of crime changes as prison population or policing levels are altered. These numbers are entered by the user on the input screen shown in Exhibit 28.

One particular problem with the "Part 1" UCR crime data is that they do not align directly with how some states, including Washington, define felony crimes. In Washington, this applies to two types of crimes in particular: felony sex crimes and theft/larceny. The UCR sex offense data only include rapes of females over the age of 12. In addition to this obvious limitation in the UCR data, there are other felony sex crimes (e.g., child molestation), defined by the Revised Code of Washington, that are not included in the UCR rape category. Similarly, the UCR data include some types of theft crimes

[84] Marvell, T. B. (2010). Prison Population and Crime. *Handbook on the Economics of Crime*, B. L. Benson & P. R. Zimmerman (Eds.). Cheltenham, UK: Edward Elgar Publishing.

[85] Lim, H., Lee, H., & Cuvelier, S.J. (2010). "The Impact of Police Levels on Crime Rates: A Systematic Analysis of Methods and Statistics in Existing Studies." Asia Pacific Journal of Police & Criminal Justice, 8(1), 49-82.

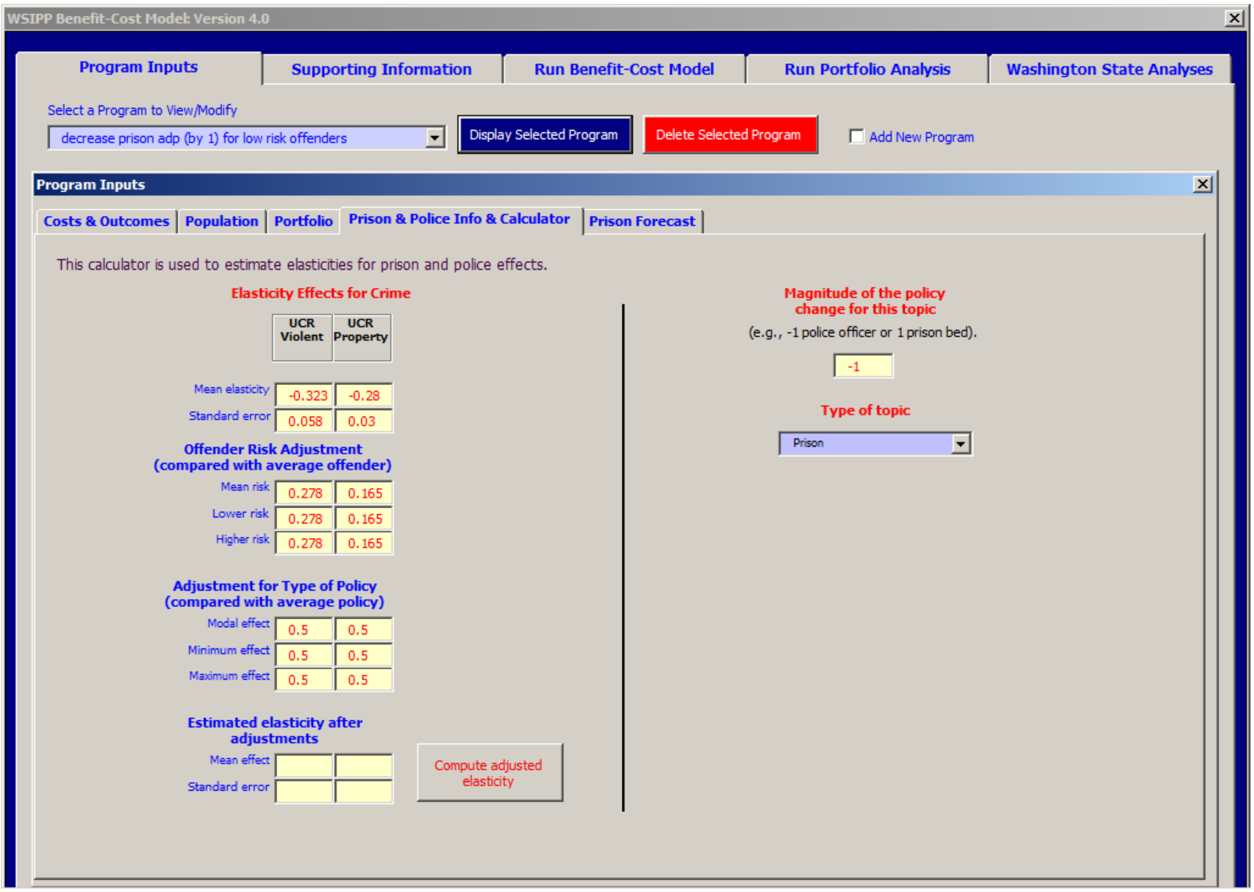
[86] See, for example, Marvell, 2010. See also, W. Spelman (2008). Specifying the relationship between crime and prisons, *Journal of Quantitative Criminology, 24*, 149-178.

[87] Durlauf, S. N., & Nagin, D. S. (2010). The Deterrent Effect of Imprisonment NBER 5/07/10, downloaded from: www.nber.org/chapters/c12078

[88] Bureau of Justice Statistics, United States Department of Justice, Ncvs http://www.bjs.gov/index.cfm?ty=dcdetail&iid=245

that are below the threshold of felony theft in Washington. Therefore, in order to draw policy conclusions from research estimating equations 4.13 and 4.14 with UCR data, it is necessary to adjust the estimates to account for these limitations in the UCR data. These adjustments are entered by the user on the input screen shown in Exhibit 31.

Exhibit 31



The policy variables: average daily prison population and the number of police officers. In virtually all studies in these two research literatures, the policy variable analyzed is either average daily prison population or the number of police officers. In the prison studies, this is often measured by counting the total number of inmates at some point during a year. Similarly, for the policing studies, the policy variable is usually measured with counts of commissioned police officers also taken at some point during a year.

Measuring prison ADP with the total number of offenders is necessary in cross-state analyses because total ADP is usually the only consistent information available to researchers. In lieu of the "average" prison population, however, it would be more useful to measure policy-relevant categories of offenders such as those convicted of violent, property, or drug offenses, or defining offenders based on an actuarial risk assessment as high risk, moderate risk, or lower risk offenders.

It would also be better if the studies could measure the two ways that policies can influence prison ADP: the probability of going to prison given a conviction, and the length of stay in prison given a prison sentence. As noted later, these separate policies are likely to have substantially different effects.

Unfortunately, because these more detailed categories are not available consistently across states, the typical study only includes a measure of total ADP and, thereby, only measures the average effect on crime of the average offender sentenced to prison from the average policy change that affects ADP. Thus, without adjustment, the overly general findings from a typical research study implementing equation 4.13 limits the practical policy relevance in analyzing the types of specific sentencing policies frequently advanced by policymakers.[89] Additionally, the "average" effect may under- or over-estimate the impact on crime of a particular policy proposal.

[89] Durlauf & Nagin (2010).

Two adjustments to address the "average offender" and "average policy" limitations. These limitations pose at least two problems that limit the usefulness of models like equation 4.13 to inform actual policy choices facing legislatures.

First, policy decisions to raise or lower ADP are not usually across-the-board or "average" decisions applied to all offenders. A legislature will rarely raise sentences for all types of crimes by a uniform amount, nor will a legislature typically lower sentences uniformly for all types of crimes (although this has been done in some states). A legislature will more often adjust sentencing statutes for particular types of crimes or for different offender risk levels, rather than adopt across-the board changes. For example, if a legislature allows executive agencies to grant early release from prison, the policy will most often be limited to offenders with certain types of criminal history or for offenders with particular risk-for-reoffense levels.

Fortunately, additional information can be obtained about the criminal propensities of different types of offenders, the types of crimes they commit, and their overall risk level for committing crimes. As noted later, we use this information to make an adjustment to address, at least partially, the policy relevance of the "average offender" limitation in the current level of research.

The second significant reason why an adjustment needs to be made to the prison or police average estimates is that not all policies that affect prison ADP or policing levels appear to have an equal effect on crime. Nagin (2013) notes that ADP "is not a policy variable per se; rather, it is an outcome of the sanction policies dictating who goes to prison and for how long—namely, the certainty and severity of punishment." [90]

Durlauf and Nagin (2010) provide a useful review and analysis of the research literature on the two sentencing factors that determine a state's ADP: the probability of a sentence to prison given a conviction, and the severity of the sentence in terms of length of prison stay. Each of these sentencing parameters—the certainty of punishment and the severity of punishment—are affected by different sentencing policies. And, as Durlauf and Nagin found, the research literature indicates that the two types of policies are likely to have quite different effects on crime. They state:

> *The key empirical conclusion of our literature review is that there is relatively little reliable evidence of variation in the severity of punishment having a substantial deterrent effect but that there is relatively strong evidence that variation in the certainty of punishment has a large deterrent effect.*[91]

Thus, when estimating how a specific policy proposal to change ADP affects crime with the estimated coefficients from equation 4.13, it is likely to matter if the policy being analyzed affects ADP based on a change to the certainty or severity of imprisonment. Using the Durlauf and Nagin results, one would conclude that ADP's "average" elasticity from 4.13 for a sentencing policy that affects the certainty of punishment would be higher than the elasticity for a sentencing policy that affects the length of prison stay. While the current state of research may not allow a clear delineation of the magnitude of these effects, the direction is clear based on the review of the literature by Durlauf and Nagin. Therefore, to make the results of the literature more relevant for policy purposes, we make adjustments, described later, to the coefficients from equation 4.13 to deal with this "average policy" limitation in the current research literature.

In summary, these two factors—the "average offender" and "average policy" limitations—imply that the coefficients obtained from equations such as 4.13 can be thought of as only rough guides for the effectiveness of sentencing changes. The coefficients obtained from these equations need to be adjusted to better estimate the specific policy choices available to legislatures. Adjustments need to reflect: (1) the heterogeneity of criminal propensities among offenders and that legislatures usually adjust sentencing policies differentially for different types of crimes, and (2), that the type of sentencing policy is likely to affect crime differentially depending on whether total prison ADP is achieved with policy changes affecting the certainty or the severity of punishment. Our modeling approach attempts to account for these necessary policy adjustments.

These limitations that affect the prison research literature also apply to the policing literature in that the research studies typically measure policing levels with a simple count of the total number of officers, not by type of officer employed or how they are deployed in the community.

In order to compute benefit-cost estimates, the meta-analyzed elasticities reported in the aforementioned WSIPP report on prison and police need to be converted into the number of crimes avoided or incurred with a particular change in prison or policing levels. Additionally, to address the aforementioned limitations in the policy-relevance of the overall elasticities, we implement two adjustments.

To begin, the usual calculation of marginal effects from the elasticities obtained with log-log crime models is obtained with equation 4.15 for the effect of prison on crime, and equation 4.16 for the effect of police on crime.

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[90] Nagin, D. (2013). Deterrence in the Twenty-first Century: A Review of the Evidence. *Crime and Justice: A Review of Research*. Chicago, IL: University of Chicago Press.
[91] Durlauf & Nagin (2010): p. 45 of the NBER draft chapter.

$$(4.15)\ \ \Delta C_t = \frac{E_t \times \left(\frac{C_t}{ADP}\right)}{RR_t} \qquad (4.16)\ \ \Delta C_t = \frac{E_t \times \left(\frac{C_t}{POL}\right)}{RR_t}$$

In equations 4.15 and 4.16, the change in the number of crimes, ΔC, for a particular type of crime, t, is estimated with: (1) E, the crime-prison elasticity or the crime-police elasticity for a particular type of crime, t, obtained from the relevant meta-analysis reported in the aforementioned WSIPP report on prison and police; (2) the reported level of crime, C, for a particular crime type, t; (3) the incarceration rate, ADP, or the level of police employment, POL; and (4) the reporting rate to police by crime victims, RR, for a particular type of crime, t. In many studies, the marginal effects are often calculated at the mean values for ADP, POL, C_t, and RR_t over the time series. For policy purposes, however, it is more relevant to use the most recent values for these variables. The data for ADP and POL are entered by the user on the input screen shown in Exhibit 25.

As noted earlier, the UCR definition of Part 1 crimes may not match a state's current definition of felony crimes. Therefore, we make adjustments to the reported UCR crimes for two types of crimes, sex offenses and larceny/theft, to more closely align the UCR definitions with current law definitions in Washington.

$$(4.17)\ \ C_t = UCR_t \times UCRAdj_t$$

In this analysis, we implement equations 4.15 and 4.16 for two types of crime: violent crime and property crime. Further, we make two adjustments to the meta-analyzed elasticities, E_t, as reported in the aforementioned WSIPP report on prison and police. Therefore, we modify equations 4.15 and 4.16 as follows:

$$(4.18)\ \ \Delta C_v = \frac{(E_v \times R_v \times P_v) \times \left(\frac{C_v}{ADP}\right)}{RR_v} \qquad (4.19)\ \ \Delta C_v = \frac{(E_v \times R_v \times P_v) \times \left(\frac{C_v}{POL}\right)}{RR_v}$$

$$(4.20)\ \ \Delta C_p = \frac{(E_p \times R_p \times P_p) \times \left(\frac{C_p}{ADP}\right)}{RR_p} \qquad (4.21)\ \ \Delta C_p = \frac{(E_p \times R_p \times P_p) \times \left(\frac{C_p}{POL}\right)}{RR_p}$$

Two adjustments. These equations for violent and property crimes modify the basic elasticities to account for how a particular sentencing policy change being analyzed may be focused on offenders with different risk-for-reoffense classifications, R, and how the specific policy being analyzed, P, may influence average ADP through its effect on the certainty or severity of punishment. As noted earlier, both R and P are likely to be important in estimating the effect of prison or police on crime, yet the studies used in the meta-analytic determination of E only measure average effects. Without adjustment, the total effect, measured by E, masks important factors that specific sentencing or policing policies try to achieve.

The risk adjustment, *R*. The first adjustment factor is designed to modify E to account for how particular policy proposals may be designed for offenders with different risk-for-reoffense probabilities. For example, some policy changes might be focused on early release from prison policies for lower-risk offenders. The basic elasticity, E, was estimated from research studies that measure all offenders that make up total prison ADP. If the models had been able to use "lower-risk" ADP instead of total ADP in the estimations, then E would have been different (particularly if the main effect being measured is the incapacitation of specific offenders, rather than general deterrence). The multiplicative adjustment factor, R, provides a way to model this likely result.

To estimate R, we report in the aforementioned WSIPP report on prison and police the recidivism rates of offenders released from prison in Washington State. We compute simple ratios of recidivism rates that indicate the relative likelihood of recidivism for offenders with different risk-for-reoffense levels, compared to all offenders as a group. These ratios are then used as risk adjustment multipliers, R, in equations 4.18-4.21.

The policy adjustment, *P*. As noted earlier, there are two ways policies can affect total ADP: the probability of going to prison given a conviction, and the length of stay given a prison sentence. The first factor implies punishment certainty while the second more closely reflects punishment severity. These two factors are likely to have different effects on crime, yet the overall elasticity, E, estimated with current research using total ADP, is unable to distinguish the separate effects. Therefore, equations 4.18, 4.19, 4.20, and 4.21 implement a second multiplicative adjustment, P, to account at least partially for this limitation in the current state of research.

For example, if a sentencing policy being analyzed involves reducing ADP by lowering length of stay, and if there is evidence that changes in prison length of stay has a smaller effect on crime than the probability of prison (given a conviction), then the policy multiplier, P, would be set at value less than one.

Estimating large changes in ADP or POL. Since the computation of marginal effects from equations 4.18, 4.19, 4.20, and 4.21 is designed for small unit changes in ADP or POL, and since the results will typically be used in practice to estimate the effects of larger policy changes in ADP or POL, the computation of the total marginal crime effect is estimated iteratively, one ADP or POL at a time. Equations 4.22, 4.23, 4.24, and 4.25 implement this iterative process for violent and property crime marginal effects. The equation sums the change in crimes for the (absolute value) of a total sentencing change or police change. For a policy that raises or lowers total prison ADP_T or total police levels $POL_{T,}$ the change in crime by type, *ΔC_V or ΔC_p*, is calculated with the estimate of the adjusted elasticity for that type of crime, E times R times P, multiplied by the total crime of each type after each unit iteration of the total ADP or POL change. If ADP is increased by a policy change, then ADP increases (+) by one unit for each iteration *a*; if ADP is decreased by a policy change, then ADP decreases (-) by one unit for each iteration, *a*.

$$(4.22)\ \Delta C_v = \frac{\sum_{a=1}^{|\Delta ADP_T|} (E_v \times R_v \times P_v) \times \frac{[C_{v(a)} + (\Delta C_{v(a-1)})]}{(ADP_T \pm a)}}{RR_v} \qquad (4.23)\ \Delta C_v = \frac{\sum_{a=1}^{|\Delta POL_T|} (E_v \times R_v \times P_v) \times \frac{[C_{v(a)} + (\Delta C_{v(a-1)})]}{(POL_T \pm a)}}{RR_v}$$

$$(4.24)\ \Delta C_p = \frac{\sum_{a=1}^{|\Delta ADP_T|} (E_p \times R_p \times P_p) \times \frac{[C_{p(a)} + (\Delta C_{p(a-1)})]}{(ADP_T \pm a)}}{RR_p} \qquad (4.25)\ \Delta C_p = \frac{\sum_{a=1}^{|\Delta POL_T|} (E_p \times R_p \times P_p) \times \frac{[C_{p(a)} + (\Delta C_{p(a-1)})]}{(POL_T \pm a)}}{RR_p}$$

For example, for a policy that decreases prison ADP by 100 units, equations 4.22 and 4.24 are calculated 100 times, each time calculating the marginal crime effect after substituting a one unit reduction in ADP and the new level of the crime variable after the previous delta crime has been computed.

For a number of the benefit-cost calculations that follow, we are interested in total violent or property crime effects as described with equations 4.22, 4.23, 4.24, and 4.25. Total crime changes are used, for example, in computing the victim costs of crimes incurred or the victim benefits of crime avoided when policies change. For some calculations, however, we are only interested in computing the taxpayer costs of the criminal justice system and, hence for these calculations we are only interested in crimes reported to police. Equations 4.26 and 4.27 set these reported-crime estimates, ΔRC_v and ΔRC_p.

$$(4.26)\ \Delta RC_v = \Delta C_v \times RR_v$$

$$(4.27)\ \Delta RC_p = \Delta C_p \times RR_p$$

Modeling risk in the marginal crime effects. For the key inputs in equations 4.22-4.25, we model risk using a Monte Carlo process. For the elasticity parameter, E, we use the standard errors from the meta-analyses reported in the aforementioned WSIPP report on prison and police. We also use low, modal, and high parameters for the risk, R, and policy, P, adjustments. In Monte Carlo simulation, these parameters are used to randomly draw from a normal probability density distribution (for the elasticity estimate, E) and triangular probability density distributions (for the risk and policy adjustments, R and P). We run the Monte Carlo process 10,000 times and compute the mean-adjusted elasticity along with its standard deviation from the 10,000 Monte Carlo runs.

Estimating the monetary value of changes in current crime from prison and police changes. The process described above produces estimates of the number of crimes avoided or incurred when a prison or policing policy is changed. The direction of the change in crimes depends, of course, on the policy being analyzed and the sign on the elasticities in the aforementioned WSIPP report on prison and police. The monetary valuation of the change in the number crimes centers on two types: victim costs or benefits and taxpayer costs or benefits.

Victim costs or benefits. The victim costs or benefits are estimated with:

$$(4.28)\ \Delta Victim\$ = \Delta C_v \times VictimPerUnit\$_v + \Delta C_p \times VictimPerUnit\$_p$$

The change in the total value of victim costs, *$\Delta Victim\$$,* is the sum of the change in the number of violent and property victimizations from equations 4.22-4.25, *ΔC_v and ΔC_p* times, respectively, the marginal victim cost per violent and property victimization, *$VictimPerUnit\$_v$ and $VictimPerUnit\$_p$*. The per unit costs are denominated in a common base year's dollars used for all monetary valuations in the benefit-cost analyses. In Monte Carlo simulation, a triangular probability density distribution is used to model uncertainty in the per unit victim costs.

Criminal justice system costs or benefits. When crime is increased or reduced, taxpayers can expect to pay more or less, respectively, from the policy change. The calculation of these amounts are done for police expenses; court-related expenses including court staff, prosecutor and defender staff; jail sanction costs; prison costs; and community supervision costs for jail-based or prison-based sentences. The following equations are used to calculate the change in expenses for each part of the criminal justice system.

$$(4.29)\ \ \Delta Police\$ = \Delta RC_v \times \frac{Arrest_v}{RC_v} \times PolicePerArrest\$_v + \Delta RC_p \times \frac{Arrest_p}{RC_p} \times PolicePerArrest\$_p$$

$$(4.30)\ \ \Delta Court\$ = \Delta RC_v \times \frac{Conviction_v}{RC_v} \times CourtPerConviction\$_v + \Delta RC_p \times \frac{Conviction_p}{RC_p} \times CourtPerConviction\$_p$$

$$(4.31)\ \ \Delta Jail\$ = \Delta RC_v \times \frac{JailLOS_v}{RC_v} \times JailPerYear\$_v + \Delta RC_p \times \frac{JailLOS_p}{RC_p} \times JailPerYear\$_p$$

$$(4.32)\ \ \Delta Prison\$ = \Delta RC_v \times \frac{PrisonLOS_v}{RC_v} \times PrisonPerYear\$_v + \Delta RC_p \times \frac{PrisonLOS_p}{RC_p} \times PrisonPerYear\$_p$$

$$(4.33)\ \ \Delta JailCS\$ = \Delta RC_v \times \frac{JailCSLOS_v}{RC_v} \times JailCSPerYear\$_v + \Delta RC_p \times \frac{JailSuperLOS_p}{RC_p} \times JailCSPerYear\$_p$$

$$(4.34)\ \ \Delta PrisonCS\$ = \Delta RC_v \times \frac{PrisonCSLOS_v}{RC_v} \times PrisonCSPerYear\$_v + \Delta RC_p \times \frac{PrisonCSLOS_p}{RC_p} \times PrisonCSPerYear\$_p$$

For each segment of the criminal justice system, the change in expenses is the sum the change in the number of reported violent and property victimizations from equations 4.26 and 4.27, ΔRC_v *and* ΔRC_p times, respectively, the probability that a reported crime uses resources in each criminal justice segment, times the marginal cost of that segment per violent and property victimization. For jail and prison length of stay and for the length of stay on community supervision for jail-based and post-prison-based segments, the parameters are conditional on the probability of a conviction given a reported crime. The per unit costs are denominated in a common "base" year's dollars used for all monetary valuations in the benefit cost analyses. In Monte Carlo simulation, a triangular probability density distribution is used to model uncertainty in the marginal per unit criminal justice costs.

Equation 4.35 sums up the total change in cri me-related costs from equations 4.28 to 4.34 and measures the effect of a policy change on current crime related costs or benefits.

$$(4.35)\ \Delta CurrentCrime\$ = \Delta Victim\$ + \Delta Police\$ + \Delta Court\$ + \Delta Jail\$ + \Delta Prison\$ + \Delta JailCS\$ + \Delta PrisonCS\$$$

4.3 Valuation of Child Abuse and Neglect Outcomes

WSIPP's benefit-cost model contains procedures to estimate the monetary value of changes in the occurrence of child abuse and neglect (CAN), as well as the monetary value of changes in out-of-home placement (OoHP) in the child welfare system. This section of the Benefit-Cost Technical Manual describes WSIPP's current procedures to estimate the monetary benefits of program-induced changes in CAN and OoHP.

In general, analysts have constructed two types of studies to estimate the costs of CAN: "prevalence-based" studies and "incidence-based" studies. Prevalence costing studies look backward and ask: How much does CAN cost society today, given all current and past CAN among people alive in a state or country?[92] Incidence costing studies look forward and ask: How much benefit could be obtained in the future if CAN was reduced? Both approaches use some of the same information, but assemble it different ways. Incidence-based studies are more useful for estimating the expected future benefits and costs of policy choices; WSIPP's model uses an incidence-based approach.

This component of WSIPP's benefit-cost model is designed to ascertain whether or not there are effective, economically attractive policy options that can reduce CAN and OoHP if implemented well. WSIPP's model includes estimates for the value of reducing a substantiated child abuse and neglect (CAN) case, from the perspective of the victim, and to society at large. In addition, we estimate the value of avoiding out-of-home placements in foster care from the perspective of the taxpayer. The direct benefits are derived by calculating the costs that are incurred with the incidence of a child abuse and neglect case, or an occurrence of placement out-of-home.

CAN costs are a function of three principal components: the expected value of public costs associated with a substantiated CAN case (e.g., child welfare system and court costs) and an estimate of the medical, mental health, and quality of life costs associated with the victim of CAN. Other long-term costs that are causally linked to the incidence of CAN are discussed in Chapter 5. OoHP costs are derived from the expected value public costs of an out-of-home placement, conditional on that placement occurring. As the costs for OoHP are most often a function of CAN-related participation in the child welfare system, we most frequently refer to the "CAN model" when describing our computations below.

Limitations of Our Methods for Valuing Reductions in CAN and OoHP

In the current benefit-cost model, we do not estimate the benefits of reducing CAN to the children of CAN victims. Our model is presently limited to effects on the two generations of CAN prevention or intervention program participants: the parent and the child (potential victim). Some research has demonstrated that CAN victims are more likely to perpetrate abuse or neglect on their own children;[93] we are unable to monetize those effects at this time.

[92] See for example, Wang, C. T. & Holton, J. (2007). *Total estimated cost of child abuse and neglect in the United States*. Chicago: Prevent Child Abuse America. Retrieved June 30, 2011 from: http://www.preventchildabuse.org/about_us/media_releases/pcaa_pew_economic_impact_study_final.pdf

[93] Whipple, E. E. & Webster-Stratton, C. (1991). The role of parental stress in physically abusive families. *Child Abuse & Neglect, 15*(3), 279-291; Hunter, R. S., Kilstrom, N., Kraybill, E. N., & Loda, F. (1978). Antecedents of child abuse and neglect in premature infants: A prospective study in a newborn intensive care unit. *Pediatrics, 61*(4), 629-635; Kim, J. (2009). Type-specific intergenerational transmission of neglectful and physically abusive parenting behaviors among young parents. *Children and Youth Services Review, 31*(7), 761-767; Belsky, J. (1993). Etiology of child maltreatment: A developmental-ecological analysis. *Psychological Bulletin, 114*(3), 413-434.

Second, there is a higher risk of death among CAN victims compared to other children. In our model, we do not monetize these deaths explicitly, but rather through our valuation of victim costs. Because we do not model death from CAN explicitly, we do not compute benefits derived from death adjusted life years (DALY) or the value of a statistical life. For victimization costs that include the probability of death from CAN, we use estimates from Miller, Fisher, and Cohen, which are discussed in some detail below.[94]

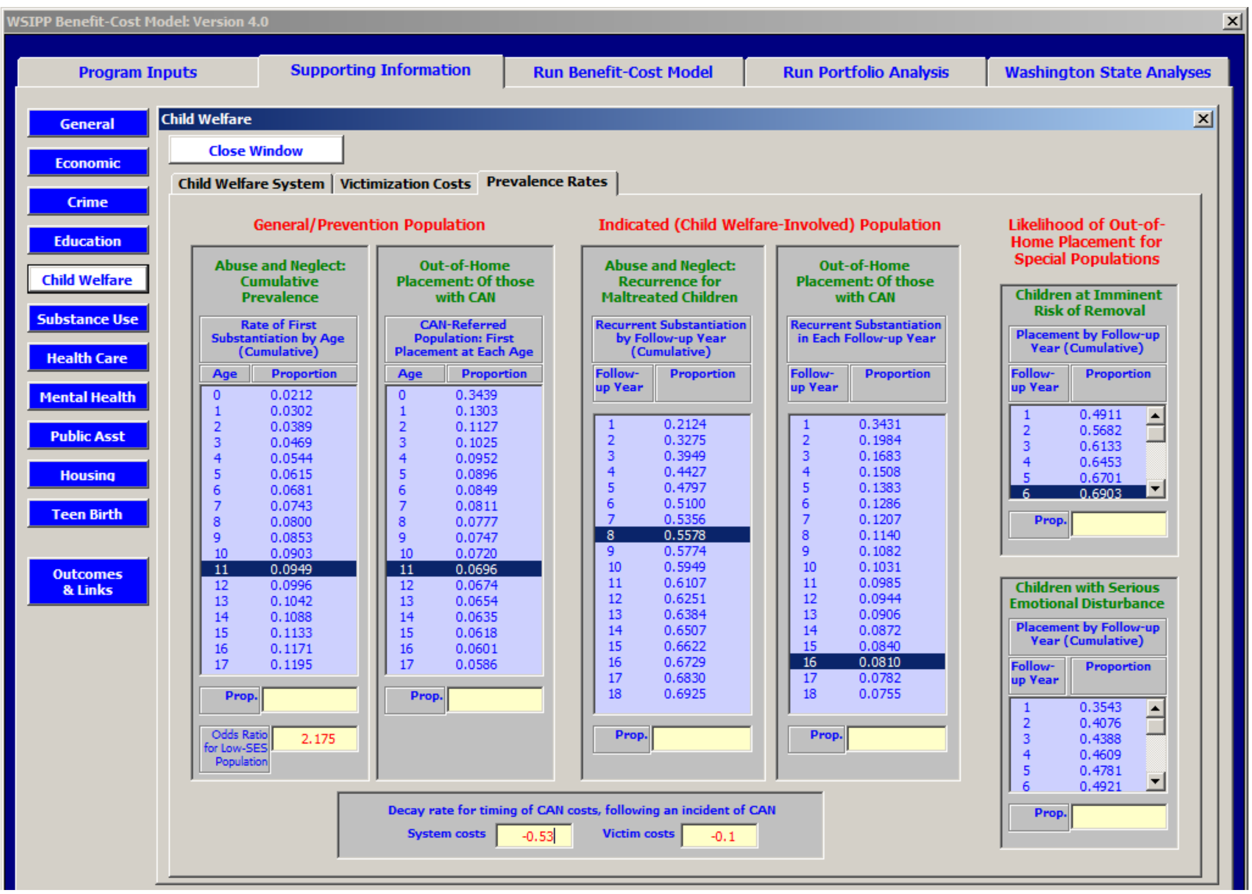
Finally, our model describes the direct result of a reduction in CAN by calculating the reduced public spending by the agencies that process CAN cases and a reduction in CAN victimization costs. In addition to these direct benefits, however, a reduction in CAN can also be expected to have an indirect causal linkage to several other outcomes monetized in this benefit-cost analysis, as described in section 4.3c of this Chapter.

4.3a Input Screens for CAN Parameters

The CAN model is driven with a set of parameters describing various aspects of CAN epidemiology, participation in the child welfare system, and linked relationships with other outcomes. These input parameters are shown in the following three screen shots. In addition, there are several other input parameters used in the CAN model that are general to WSIPP's overall benefit-cost model; these are discussed elsewhere in this Chapter. In the following sections, the sources for the parameters and the computational routines are described.

Exhibits 32, 33, and 34 display the parameters for the analysis of child abuse and neglect and out-of-home placement in the child welfare system. Each is described in detail below.

Exhibit 32



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[94] Miller, T. R., Fisher, D. A., & Cohen, M. A. (2001). Costs of juvenile violence: Policy implications. *Pediatrics, 107*(1), DOI: 10.1542/peds.107.1.e3.

Exhibit 33

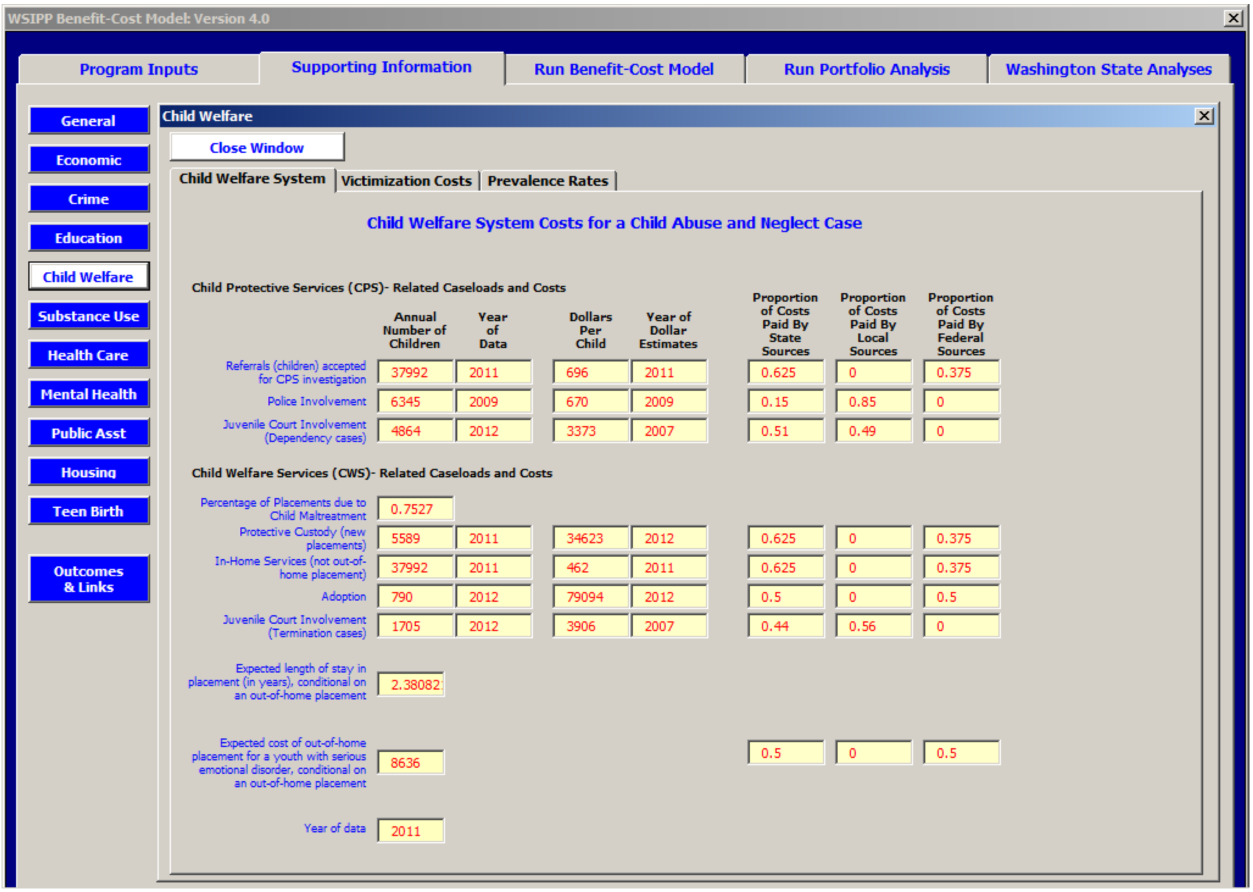
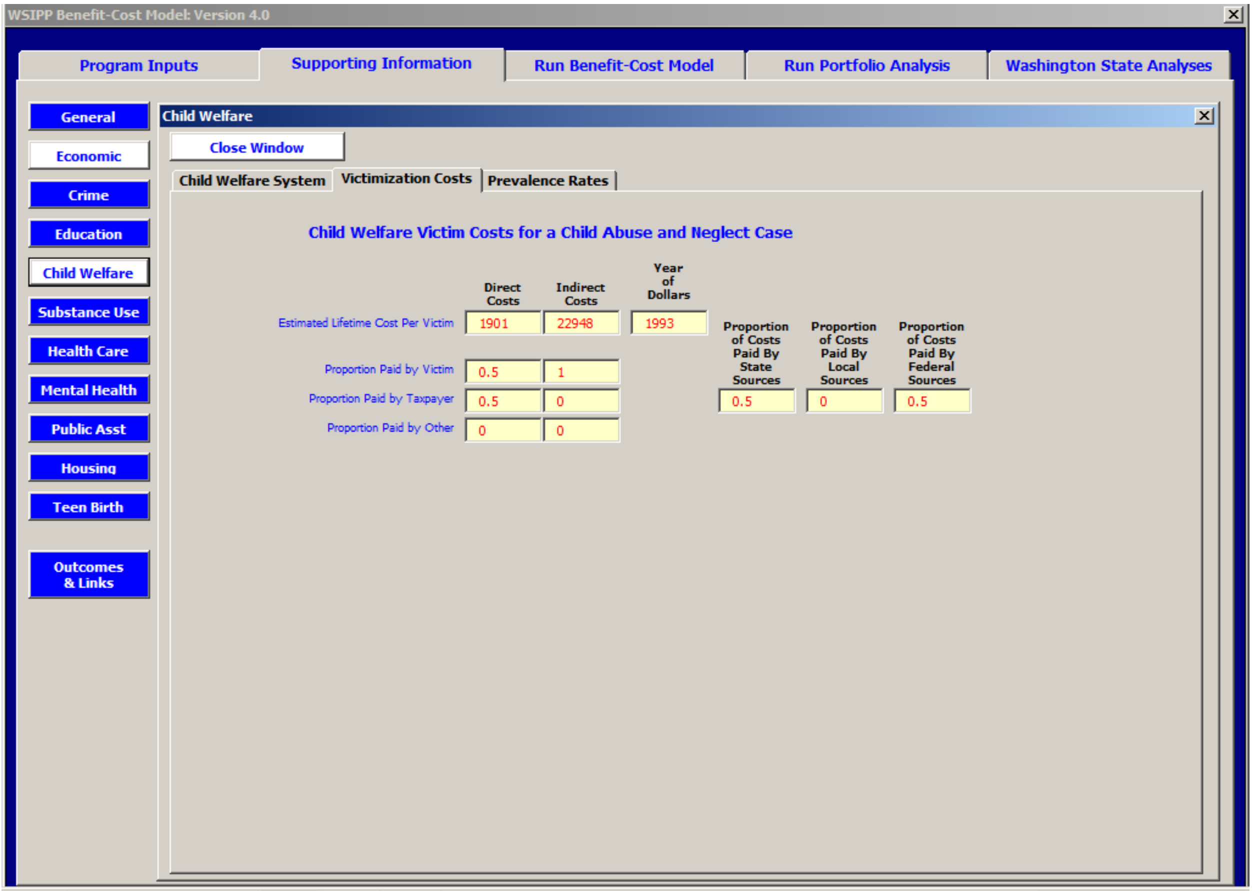

WSIPP Benefit-Cost Model: Version 4.0
Program Inputs
Supporting Information
Run Benefit-Cost Model
Run Portfolio Analysis
Washington State Analyses
General
Economic
Crime
Education
Child Welfare
Substance Use
Health Care
Mental Health
Public Asst
Housing
Teen Birth
Outcomes & Links
Child Welfare
Close Window
Child Welfare System
Victimization Costs
Prevalence Rates
Child Welfare System Costs for a Child Abuse and Neglect Case
Child Protective Services (CPS)- Related Caseloads and Costs
Annual Number of Children
Year of Data
Dollars Per Child
Year of Dollar Estimates
Proportion of Costs Paid By State Sources
Proportion of Costs Paid By Local Sources
Proportion of Costs Paid By Federal Sources
Referrals (children) accepted for CPS investigation
37992
2011
696
2011
0.625
0
0.375
Police Involvement
6345
2009
670
2009
0.15
0.85
0
Juvenile Court Involvement (Dependency cases)
4864
2012
3373
2007
0.51
0.49
0
Child Welfare Services (CWS)- Related Caseloads and Costs
Percentage of Placements due to Child Maltreatment
0.7527
Protective Custody (new placements)
5589
2011
34623
2012
0.625
0
0.375
In-Home Services (not out-of-home placement)
37992
2011
462
2011
0.625
0
0.375
Adoption
790
2012
79094
2012
0.5
0
0.5
Juvenile Court Involvement (Termination cases)
1705
2012
3906
2007
0.44
0.56
0
Expected length of stay in placement (in years), conditional on an out-of-home placement
2.38082
Expected cost of out-of-home placement for a youth with serious emotional disorder, conditional on an out-of-home placement
8636
0.5
0
0.5
Year of data
2011

Exhibit 34



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Estimated Lifetime Cost Per Victim
1901
22948
1993
Proportion of Costs Paid By State Sources
Proportion of Costs Paid By Local Sources
Proportion of Costs Paid By Federal Sources
Proportion Paid by Victim
0.5
1
Proportion Paid by Taxpayer
0.5
0
0.5
0
0.5
Proportion Paid by Other
0
0

4.3b CAN Parameters: Prevalence for Prevention and Intervention Programs, Timing of Costs

WSIPP's CAN model begins by analyzing the epidemiology of CAN to produce estimates of the cumulative likelihood of experiencing child abuse or neglect. An estimate of the cumulative prevalence of CAN is central to the benefit-cost model because it becomes the "base rate" of CAN to which program or policy effect sizes are applied to calculate the change in the number of avoided CAN "units" caused by the program, over the lifetime following treatment.

Exhibit 32 displays the input form for the cumulative prevalence of CAN, from age 0 to age 17.

To compute the estimated probability of being a victim of child abuse or neglect, we use data from the National Child Abuse and Neglect Data System to calculate the one-year prevalence of child victims by age group.[95] In any given year, some of these cases are repeat cases from previous maltreatment episodes. We estimate this number by subtracting the proportion of first-time victims[96] from one. Using these two parameters to calculate the annual probability of a new substantiated child abuse or neglect case for a child from age zero to age 17, the implied lifetime prevalence rate of child abuse or neglect for the general population of children is estimated to be 11.9%. The cumulative prevalence for CAN by age, after repeat cases are accounted for, is displayed in Exhibit 32.

To test the reasonableness of this estimate, we use a second approach to calculate the lifetime prevalence. We gather other research studies that examine this question with longitudinal cohort data. Exhibit 35 summarizes these estimates. The studies measure child abuse and neglect with different definitions, for different populations, and at different times. Ignoring these variations, a simple weighted average of the studies produces an estimate of 10.6% lifetime prevalence of child abuse, slightly lower than, but similar to the estimate described in the first method above.

Some of the populations that are the focus of prevention and early intervention programs are not the general population but are, instead, from higher risk populations, often from lower socio-economic status. For the model, we estimate a parameter for this (an odds ratio applied to the annual prevalence rate for the general population) by taking a weighted average of the results of five studies that examined this question with control groups (see Exhibit 36).[97]

Exhibit 35
Lifetime Prevalence Estimates of Child Abuse and Neglect

Study	Number in study with abuse	Total number in sample	Percentage with child abuse or neglect	Notes
Total	**3,765**	**35,650**	**10.6%**	Weighted average of studies listed
Eckenrode et al., 1993	1,239	8,569	14.5%	General pop, NY, substantiated cases
Stouthamer-Loeber et al., 2001	52	506	10.3%	Inner city pop, Pittsburg, substantiated cases
Zingraff et al., 1993	10	387	2.6%	School sample, Mecklenburg, NC
Thornberry et al., 2001	213	1,000	21.3%	Rochester, NY, substantiated cases
Reynolds et al., 2003	69	595	11.6%	Chicago higher risk sample, CPS control group
MacMillan et al., 1997	1,461	9,953	14.7%	General pop, Ontario, severe, self-report
Brown et al., 1998	46	644	7.1%	General pop, non SES
Kelleher et al., 1994	378	11,662	3.2%	Five urban sites
Dodge et al., 1990	46	304	15.1%	General pop, physical abuse
Finkelhor et al., 2003	252	2,030	12.4%	One year rate

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[96] Administration on Children, Youth and Families, (2011). *Child Maltreatment 2011* Table 3-4. Retrieved August 1, 2013, from http://www.acf.hhs.gov/sites/default/files/cb/cm11.pdf.

[96] Ibid., Table 3-13.

[97] Lealman, G. T., Phillips, J. M., Haigh, D., Stone, J., & Ord-Smith, C. (1983). Prediction and prevention of child abuse—An empty hope? *The Lancet, 321*(8339), 1423-1424;. Murphey, D. A & Braner, M. (2000). Linking child maltreatment retrospectively to birth and home visit records: An initial examination. *Child Welfare, 79*(6), 711-728; Kotch, J. B., Browne, D. D., Dufort, V., Winsor, J., & Catellier, D. (1999). Predicting child maltreatment in the first 4 years of life from characteristics assessed in the neonatal period. *Child Abuse and Neglect, 23*(4), 305-319; Hussey, J. M., Chang, J. J., & Kotch, J. B. (2006). Child maltreatment in the United States: Prevalence, risk factors, and adolescent health consequences. *Pediatrics, 118*(3), 933-942; Brown, J., Cohen, P., Johnson, J. G., & Salzinger, S. (1998). A longitudinal analysis of risk factors for child maltreatment: Findings of a 17-year prospective study of officially recorded and self-reported child abuse and neglect. *Child Abuse and Neglect, 22*(11), 1065-1078.

Exhibit 36
Odds Ratios for Child Abuse and Neglect: High Risk Populations

Study	Study n	Odds ratio	High risk population
Total	**43,707**	**2.175**	**(weighted average)**
Lealman et al., 1983	2,802	3.72	Mothers under 20 OR with late prenatal care OR unmarried
Murphey & Braner, 2000	29,291	2.45	Teen mothers OR eligible for medicaid
Kotch et al., 1999	708	1.36	Receiving income support
Hussey et al., 2006	10,262	1.06	Income less than $15,000
Brown, 1998	644	1.44	Low income

For children already in the child welfare system, we also estimate the likelihood of recurrence of abuse or neglect. The results of this analysis are displayed in Exhibit 32; we use child welfare history data from Washington State to estimate, of those children who receive one accepted referral, the proportion who subsequently receive another accepted referral over time.[98] We analyze the proportion of children who have experienced a recurrence of abuse or neglect, from one year out to twelve years. We then plot a logarithmic curve with those data to predict the likelihood of a recurrence from up to 17 years after the initial incident.

Exhibit 32 also displays the base rates of out-of-home placement for various populations. For the general population, we calculate the probability of out-of-home placement at each age, given a child has an accepted CAN referral, based on a WSIPP analysis of Washington State child welfare data.[99] To compute the base likelihood of out-of-home placement for a prevention population, we multiply the likelihood of a substantiated CAN case at each age (derived from NCANDS data as described above) by the ratio of Washington-reported accepted referrals to estimated CAN cases, then by the likelihood of out-of-home placement given CAN at each age.

For the population of children already in the child welfare system, we computed the likelihood, for each year following a second accepted referral (regardless of their age at first or second accepted referral), that a child would be removed from home. For children deemed at "imminent risk" of placement, a WSIPP analysis[100] determined the risk of out-of-home placement for these children was much higher (in the first year after treatment, 50% of children labeled at "imminent risk" were indeed removed from home), so our base rate of placement for programs that serve children at imminent risk is set at 75%. The third rate in Exhibit 32 shows the cumulative likelihood over time of out-of-home placement for children with serious emotional disturbance (SED). These children are sometimes placed in intensive foster care, or in the hospital for psychiatric treatment.[101]

The final inputs in Exhibit 32 are the parameters that allow us to estimate the timing of costs incurred within the child welfare system. We have two rates of decay, one for costs within the child welfare system, and one for costs to the victim.

Within the system, costs for a case of child abuse or neglect do not occur all at once, but rather linger over time. Costs like an investigation, initial services to a family, dependency court, and so forth, occur early in the case, but child welfare services and out-of-home placements may continue for a number of years. From our data in Exhibit 33, we estimate the amount of system-related costs we would expect to be incurred within the first two years of a typical CAN case (78%). Using that figure, we calculate a rate of "decay," such that for each year after the beginning of a case, the amount of cost decayed by -0.53. That means, in the first year, 53% of the total expected costs are incurred; by the end of the second year, 78% have been incurred; 90% by the end of the third year; and so on. This decay continues for a maximum of 17 years, as child welfare system costs for out-of-home placement, courts, and child welfare services, etc., often do not continue past the age of 17.

We also estimate the amount of victim-related costs over time, expecting that these costs may linger much longer than system-related cost. Our estimated rate of decay for these costs is -0.10, which means that, relative to system costs, we expect victim costs of mental health and quality of life to be spread over a greater number of years.

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[98] WSIPP analysis of DSHS CAMIS data for FY 1998 and FY 2000 birth cohorts.

[99] Using data from DSHS CAMIS for children born between July 1, 1997 and July 1, 2008, we examined the subset of children who had at least one accepted referral at some point in their childhood (in our analysis, accepted referrals act as a proxy for substantiated CAN cases; later in the analysis we compute the ratio of accepted referrals to our estimate of substantiated CAN cases as an adjustment). We computed the proportion of children who were removed at some point subsequent to that accepted referral, by age of first accepted referral.

[100] WSIPP analysis of evaluations of the Homebuilders® model of intensive family preservation services, which serve youth at "imminent risk" of placement. For children in the comparison groups of these evaluations, approximately 75% were eventually removed from home, after being deemed at "imminent risk."

[101] We calculated the cumulative percent from two studies of Multisystemic Therapy for children with SED that followed children over more than one year. We used the data from four points in time to plot a logarithmic curve from which we projected rates of placement for up to 17 years.

Estimated child welfare system costs are displayed in Exhibit 33. The table below provides the sources for these figures, in some cases derived from Washington State data, and in other cases estimated from national data. We multiply the probability of receiving each service by the per-child cost to calculate an expected value cost for each accepted referral.

In addition, we also estimate the cost of placing children with serious emotional disturbance (SED);[102] although these children are not placed for reasons of abuse and neglect, but rather mental health problems, the programs which aim to avoid placements for this population are often provided within the child welfare system.

Exhibit 37
The Estimated Average Public Cost of a Child Protective Service Case Accepted for Investigation, State of Washington (in 2012 Dollars)

	Number of Children (1)	Probability of Receiving This Service (2)	Per-Child Cost (3)	Year of Dollar Estimates (4)	Expected Cost per Accepted Case (5)
Child Protective Services (CPS)					
Referrals (children) Accepted for Investigation	37,992[1]	**100%**	**$618**[2]	**2008**	**$653**
Police Involvement	6,345[3]	16.7%	$670[4]	2009	$118
Juvenile Court Dependency Case Involvement	4,864[5]	12.8%	$3,373[6]	2007	$472
Child Welfare Services					
Percentage of protective custody placements that are CPS cases	75.27%[7]				
Protective Custody (foster care)	5,589[8]	11.1%	$34,623[9]	2012	$3,834
In-Home Services (not out-of-home placement)	37,992[10]	2011	$462	2011	$469
Adoption	790[11]	2.1%	$79,094[12]	2012	$1,644
Juvenile Court Termination Case Involvement	1,705[13]	4.5%	$3,906[6]	2007	$192
TOTAL: Expected present value cost of an accepted CPS case (in 2012 dollars)					**$7,382**
Addendum: Expected present value cost of an out-of-home placement, conditional on an out-of-home placement					**$47,101**

Sources for Table D3.2c:
[1] Washington State DSHS Children's Administration, 2011 Year in Review, available at: http://www.dshs.wa.gov/pdf/ca/year-in-review2011.pdf.
[2] Washington State DSHS Research and Data Analysis Client Data for FY2008. Total expenditures for "Child Protective Services case management", divided by total accepted referrals.
[3] Percentage of referrals from police sources, all states, applied to total accepted referrals. From Administration on Children, Youth and Families (2011) Child Maltreatment 2011, Table 2-C, available at: http://www.acf.hhs.gov/sites/default/files/cb/cm11.pdf.
[4] Marginal operating cost of an arrest for a misdemeanor from WSIPP crime model.
[5] Washington State Office of the Administrator of the Courts, 2012, Juvenile dependency filings. Report available at http://www.courts.wa.gov/caseload/?fa=caseload.showReport&level=s&freq=a&tab=juvDep&fileID=jdpfilyr.
[6] Based on average number of hearings per case (Miller, 2004) multiplied by WSIPP analysis of average cost per hearing (based on projected length in hours, and the hourly wages for the people estimated to be involved in each hearing).
[7] Based on WSIPP analysis of DSHS Children's Administration data.
[8] AFCARS 2011, Children in Foster Care (entered care): http://cwoutcomes.acf.hhs.gov/data/downloads/pdfs/washington.pdf
[9] Calculated based on DSHS Children's Administration projected per-capita costs for FY2013. We recognize that there are additional costs of out-of-home care for children placed with relatives, such as child-only TANF payments. We are unable to estimate these costs at this time, but plan to do so in the future.
[10] DSHS Children's Administration EMIS reporting system; unduplicated counts of children served are unreported; therefore, we summed FY11 total costs for in-home services and divided by total accepted referrals for a cautious per-child estimate.
[11] WSIPP estimate of new adoption cases each year, from FY2008 DSHS Children's Administration data.
[12] WSIPP calculation of total adoption support per case, estimated from FY2012 Children's Administration data.
[13] Washington State Office of the Administrator of the Courts, 2012, Juvenile termination filings. Report available at http://www.courts.wa.gov/caseload/?fa=caseload.showReport&level=s&freq=a&tab=juvDep&fileID=jdpfilyr.

[102] The cost of out-of-home placement for SED children is based on a WSIPP analysis of Washington state data, taking into account the cost for Behavioral Rehabilitation Services (BRS--residential treatment for children) and the average length of stay in such treatment. Cost data was derived from the DSHS Children's Administration EMIS reporting system (average monthly per-child ongoing placement services costs for FY11), and length of stay was estimated from DSHS CAMIS data for children removed from home for behavior, drug, or alcohol problems between January 1, 1999 and January 1, 2005.

Expected value victim costs are derived from calculations by Miller, Fisher, and Cohen, 2001; their comprehensive analysis of the future impacts of victimization by child abuse and neglect takes into account medical, mental health, and quality of life costs, as described in Exhibit 38 below. We enter the summary taxpayer and victim costs on the input screen in Exhibit 34. These estimated totals are life cycle expected value costs per CAN crime; we use the "decay" parameter for victim costs above to "spread out" those costs over a child's life.

Exhibit 38
Medical, Mental Health, and Quality of Life Costs per Victim of Child Abuse and Neglect
1993 Dollars

	Medical and Mental Health Costs(1) (1)	Quality of Life Costs(1) (2)	Number of Victims(3) (3)
Type of Child Abuse and Neglect			
Sexual abuse	$6,327(2)	$94,506(2)	114,000
Physical abuse	$3,472(2)	$58,645(2)	308,000
Mental abuse	$2,683(2)	$21,099(2)	301,000
Serious physical neglect	$911(2)	$7,903(2)	1,236,000
Total	$1,901(4)	$22,948(4)	1,959,000
Distribution of Costs by Payer			
Percentage incurred by taxpayer	50%(5)	0%(5)	
Percentage incurred by victim	50%(5)	100%(5)	
Amount paid by taxpayer	**$951**	**$0**	
Amount paid by victim	**$951**	**$22,948**	

Sources
1. The source of the cost elements in this table is Miller, T. R., Fisher, D. A., & Cohen, M. A. (2001). Costs of juvenile violence: Policy implications. *Pediatrics, 107*(1). DOI: 10.1542/peds.107.1.e3
2. *Ibid*., Table 1. We've assumed 80 percent urban and 20 percent rural costs on the Miller et al. Table 1.
3. The source for the total U.S. number of victims: Miller, T. R., Cohen, M. A., & Wiersema. B. (1996). *Victim costs and consequences: A new look*. Research report, Table 1. Washington, DC: National Institute of Justice.
4. These totals are weighted average sums using the victim numbers in column (3).
5. WSIPP assumptions.

Sources of CAN and OoHP costs. The input screen described in Exhibit 32 allows users to input the proportion of child welfare funding from state, local, and federal sources. Washington State sources are described in Exhibit 39 below.

Exhibit 39

Proportion of Marginal Education Costs by Source

	State	Local	Federal
CPS response[1]	0.625	0.000	0.375
Police involvement[2]	0.150	0.850	0.000
Juvenile court (dependency)[3]	0.510	0.490	0.000
Protective custody (foster care)[1]	0.625	0.375	0.000
In-home services[1]	0.625	0.375	0.000
Adoption[4]	0.500	0.000	0.500
Juvenile court (termination)[3]	0.440	0.560	0.000
Out-of-home placement for children with SED[4]	0.500	0.000	0.500
Victimization (taxpayer) costs[5]	0.500	0.000	0.500

[1] For the 75% of kids who are Title IV-E eligible, we apply the Washington State FMAP rate from Federal Register /Vol. 75, No. 217 /November 10, 2010 /Notices 69083, accessed from: http://aspe.hhs.gov/health/fmap12.pdf. For the 25% of non-eligible children, we assume the state pays 100%.
[2] Justice Expenditure and Employment Extracts, 2010 - Preliminary, Tracey Kyckelhahn, Ph.D., Tara Martin, BJS Intern, July 1, 2013. NCJ 242544, Table 4: Justice system expenditure by character, state and type of government, fiscal 2010, Link: http://www.bjs.gov/index.cfm?ty=pbdetail&iid=4679. Direct current Police Protection expenditures for state and local governments for Washington State.
[3] WSIPP analysis of staff present at juvenile hearings; assume state pays 100% of Assistant Attorney General and social worker salaries, 50% of judicial officer salaries. Other staff are assumed to be fully funded by the local government.
[4] Department of Health and Human Services, *75*(217) Fed. Reg. 69083 (proposed Nov. 10, 2010), accessed from: http://aspe.hhs.gov/health/fmap12.pdf.
[5] We assume that victim costs to taxpayers will be in form of health and mental health treatment; with 50/50 FMAP split.

4.3c Linkages: CAN and Other Outcomes

WSIPP's benefit-cost model monetizes improvements in CAN, in part, with linkages between CAN and other outcomes to which a monetary value can be estimated. For example, credible research shows a causal link between the incidence of CAN and subsequent criminality of the victimized youth when he or she is older. The parameters for these linkages are obtained by a meta-analytic review of relevant research literature. For example, we estimate the relationship between CAN and later participation in crime by meta-analyzing the most credible studies that have addressed this topic. The meta-analytic process provides both an expected value effect given the weight of the evidence and an estimate of the error of the estimated effect. Both of these parameters are entered into the benefit-cost model and used when performing a Monte Carlo simulation. The linkages in the current WSIPP model are listed in Chapter 5.

4.4 Valuation of Alcohol, Illicit Drug, and Regular Tobacco Use Outcomes

WSIPP's benefit-cost model contains procedures to estimate the monetary value of changes in the disordered use of alcohol and illicit drugs, as well as the monetary value of changes in regular tobacco smoking. Illicit drugs represent a broad category of substances; the current version of WSIPP's model divides illicit drugs into (a) cannabis and (b) all other illicit drugs.[103] Analysts sometimes abbreviate alcohol, tobacco, and other drugs with the acronym ATOD. This section of the Benefit-Cost Technical Manual describes WSIPP's current procedures to estimate the monetary benefits of program-induced changes in ATOD. For WSIPP's benefit-cost model, an alcohol and illicit drug disorder reflects both abuse and dependency as defined by the Diagnostic and Statistical Manual (DSM) of the American Psychiatric Association. Regular smoking is defined as daily smoking.

In general, analysts construct two types of studies to estimate the costs of ATOD: "prevalence-based" studies and "incidence-based" studies.[104] Prevalence costing studies look backward and ask: How much does ATOD cost society today, given all current and past disordered use of ATOD among people alive in a state or country? Incidence costing studies look forward and ask: How much benefit could be obtained in the future if disordered use of ATOD can be reduced? Both approaches use some of the same information, but assemble it different ways. Incidence-based studies are more useful for estimating the expected future benefits and costs of policy choices.

WSIPP's ATOD model uses an incidence-based approach. Therefore, it is not designed to provide an estimate of the total cost to society of current and past ATOD. Other studies attempt to estimate these values.[105] For example, Rosen et al. found the total cost of alcohol in California in 2005 to be $38.5 billion in "economic" costs ($1,081 per capita) and an additional $48.8 billion in "quality of life" costs.[106] Similarly, Wickizer (2007) estimated the cost of alcohol to Washington State in 2005 to be $2.9 billion in economic costs ($466 per capita) and that illicit drugs cost Washington an additional $2.3 billion.[107] These prevalence-based total cost studies can be interesting, but they are not designed to evaluate future marginal benefits and marginal costs of specific public policy options.

The purpose of WSIPP's model is to provide the Washington State legislature with advice on whether there are economically attractive evidence-based policies that, if implemented well, can achieve reductions in the harmful use of ATOD. To do this, the model monetizes the projected life-cycle costs and benefits of programs or policies that have been shown to achieve improvements—today and in the future—in disordered ATOD. If, for example, empirical evidence indicates that a prevention program can delay the age at which young people initiate the use of alcohol, then what long-run benefits, if any, can be expected from this outcome? If an intervention program for current regular smokers can achieve a 10% reduction in the rate of smoking, then what are the life-course monetary benefits? Once computed, the present value of these benefits can be stacked against program costs to determine the relative attractiveness of different approaches to achieve improvements in desired outcomes.

The current version of the ATOD model allows the computation of the following types of avoided costs, or benefits, when a program or policy reduces probability of a person's current and future prevalence of ATOD. Depending on each particular ATOD, the following cost categories are included in WSIPP's model:

- Labor market earnings from ATOD morbidity or mortality, to the degree there is evidence that current earnings are reduced because of ATOD (morbidity), or lifetime earnings are lost because of premature death (mortality) caused by ATOD, and that the program reduces the prevalence of ATOD.
- Medical costs for hospitalization and pharmaceuticals from ATOD morbidity or mortality, to the degree that these costs are caused by ATOD, and that the program reduces the prevalence of ATOD.
- Crime costs to taxpayers and victims, to the degree that crime is estimated to be caused by ATOD, and that the program reduces the prevalence of ATOD.
- Traffic collision costs, to the degree that collisions are estimated to be caused by ATOD, and that the program reduces the prevalence of ATOD.
- Value of a statistical life (VSL) estimates, net of labor market gains, applied to the change in mortality estimated to be caused by ATOD, and that the program reduces the prevalence of ATOD.

[103] Caulkins, J. P. & Kleiman, M. A. R. (n.d.). *Drugs and crime*. Unpublished manuscript, Carnegie Mellon University, Pittsburgh, PA.
[104] Moller, L. & Matic, S. (Eds.). (2010). *Best practice in estimating the costs of alcohol: Recommendations for future studies*. Copenhagen, Denmark: WHO Regional Office for Europe.
[105] See, Harwood, H., Fountain, D., & Livermore, G. (1998). *The economic costs of alcohol and drug abuse in the United States 1992* (NIH Publication No. 98-4327). Rockville, MD: National Institutes of Health. See also, Rice, D. P., Kelman, S., Miller, L. S., & Dunmeyer, S. (1990). *The economic costs of alcohol and drug abuse and mental illness, 1985* (DHHS Pub. No.90-1694). Washington, DC: Alcohol, Drug Abuse, and Mental Health Administration.
[106] Rosen, S. M., Miller, T. R., & Simon, M. (2008). The cost of alcohol in California. *Alcoholism: Clinical and Experimental Research, 32*(11), 1925-1936. The California study uses a few incidence-based methods in addition to prevalence-based methods.
[107] Wickizer, T. M. (2007). *The economic costs of drug and alcohol abuse in Washington State, 2005*. Olympia: Washington State Department of Social and Health Services, Division of Alcohol and Substance Abuse.

4.4a Input Screens for ATOD Parameters

The ATOD model is driven with a set of parameters describing various aspects of ATOD epidemiology and linked relationships with other outcomes. These input parameters are shown in the following four screen shots. In addition, there are several other input parameters used in the ATOD model that are general to WSIPP's overall benefit-cost model, and these are discussed elsewhere in this Chapter. In the following sections, the sources for the parameters and the computational routines are described.

Exhibits 40 through 43 display the parameters for the analysis of disordered alcohol, tobacco, cannabis, and other illicit drug use.

Exhibit 40

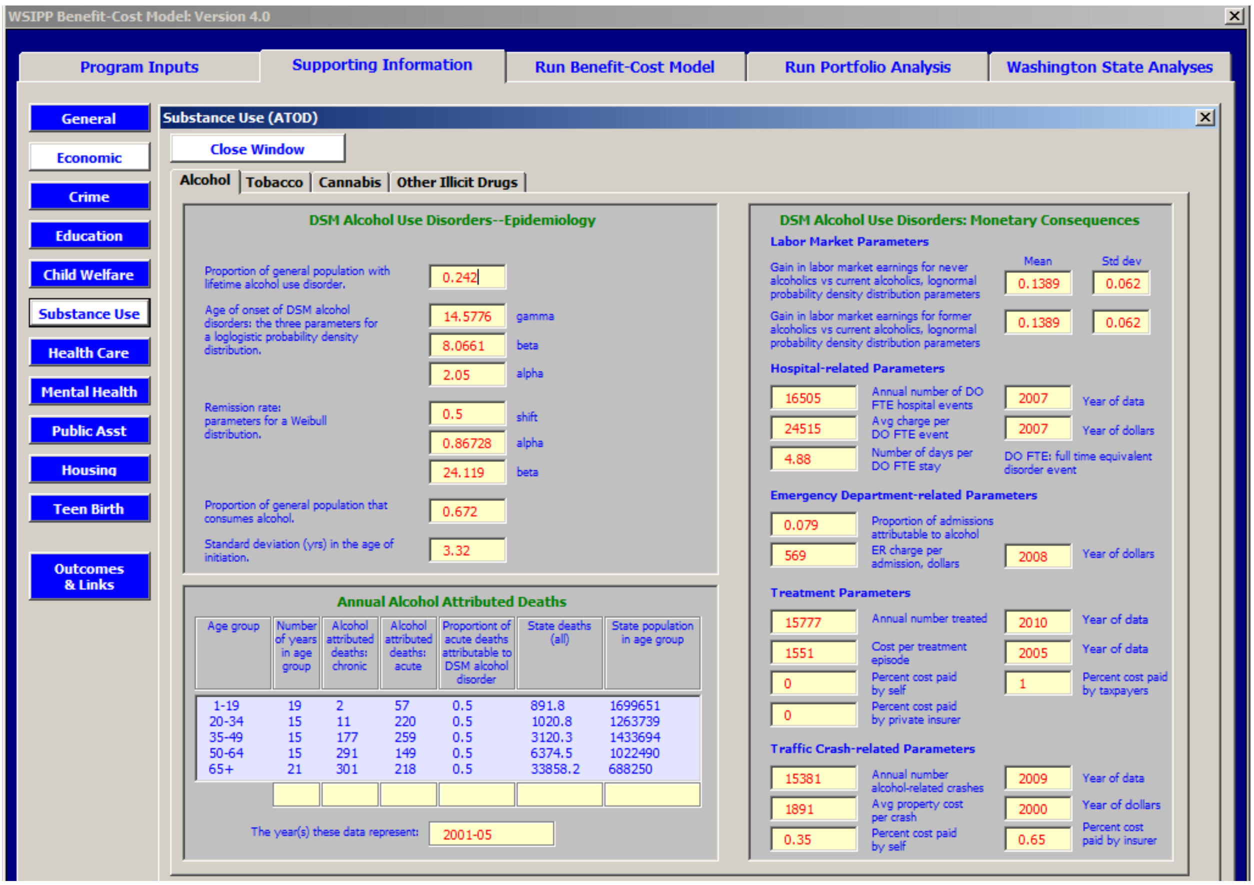
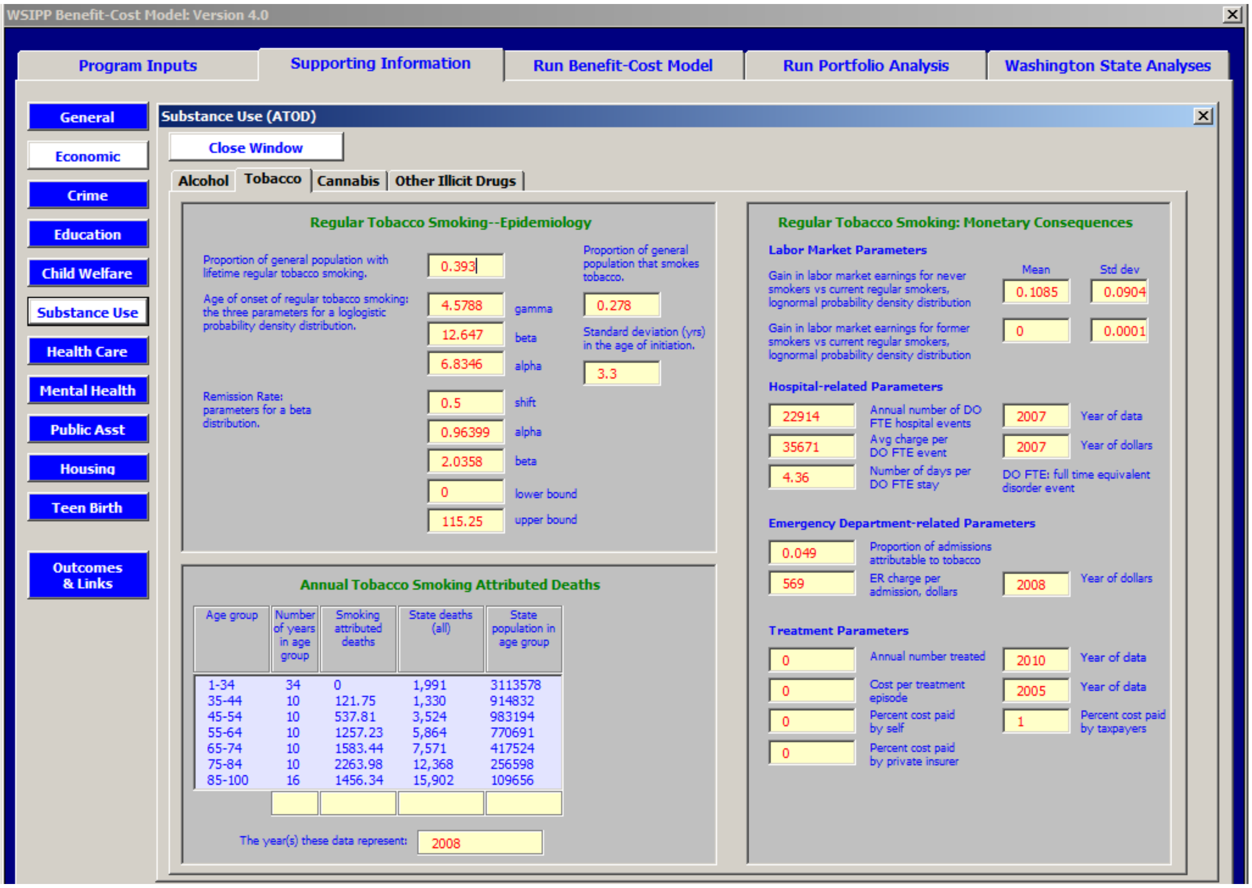


Exhibit 41



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Substance Use (ATOD)

Close Window

Alcohol | Tobacco | Cannabis | Other Illicit Drugs

Regular Tobacco Smoking--Epidemiology

Proportion of general population with lifetime regular tobacco smoking: 0.393

Proportion of general population that smokes tobacco: 0.278

Age of onset of regular tobacco smoking: the three parameters for a loglogistic probability density distribution: 4.5788 gamma; 12.647 beta; 6.8346 alpha

Standard deviation (yrs) in the age of initiation: 3.3

Remission Rate: parameters for a beta distribution: 0.5 shift; 0.96399 alpha; 2.0358 beta; 0 lower bound; 115.25 upper bound

Annual Tobacco Smoking Attributed Deaths

Age group	Number of years in age group	Smoking attributed deaths	State deaths (all)	State population in age group
1-34	34	0	1,991	3113578
35-44	10	121.75	1,330	914832
45-54	10	537.81	3,524	983194
55-64	10	1257.23	5,864	770691
65-74	10	1583.44	7,571	417524
75-84	10	2263.98	12,368	256598
85-100	16	1456.34	15,902	109656

The year(s) these data represent: 2008

Regular Tobacco Smoking: Monetary Consequences

Labor Market Parameters

	Mean	Std dev
Gain in labor market earnings for never smokers vs current regular smokers, lognormal probability density distribution	0.1085	0.0904
Gain in labor market earnings for former smokers vs current regular smokers, lognormal probability density distribution	0	0.0001

Hospital-related Parameters

22914 Annual number of DO FTE hospital events; 2007 Year of data

35671 Avg charge per DO FTE event; 2007 Year of dollars

4.36 Number of days per DO FTE stay

DO FTE: full time equivalent disorder event

Emergency Department-related Parameters

0.049 Proportion of admissions attributable to tobacco

569 ER charge per admission, dollars; 2008 Year of dollars

Treatment Parameters

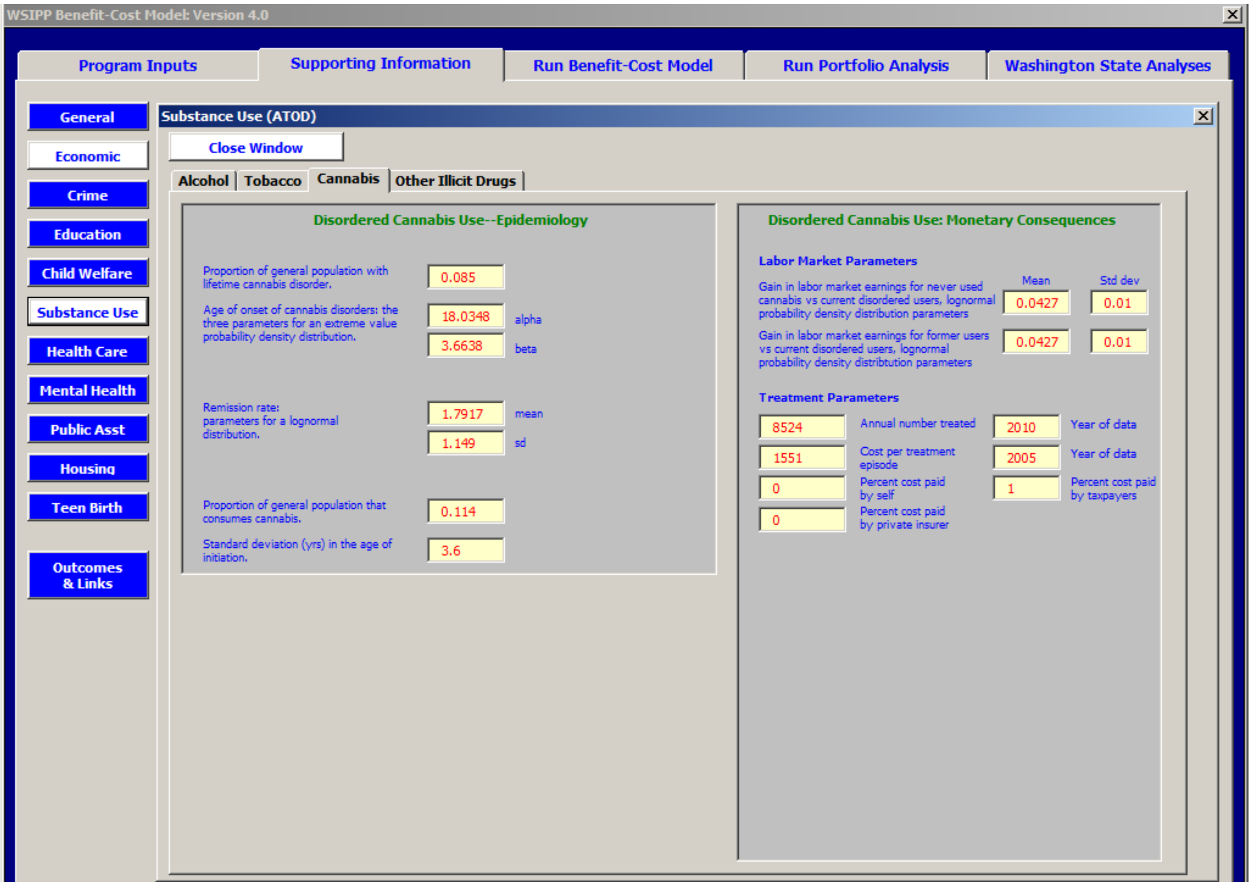
0 Annual number treated; 2010 Year of data

0 Cost per treatment episode; 2005 Year of data

0 Percent cost paid by self; 1 Percent cost paid by taxpayers

0 Percent cost paid by private insurer

Exhibit 42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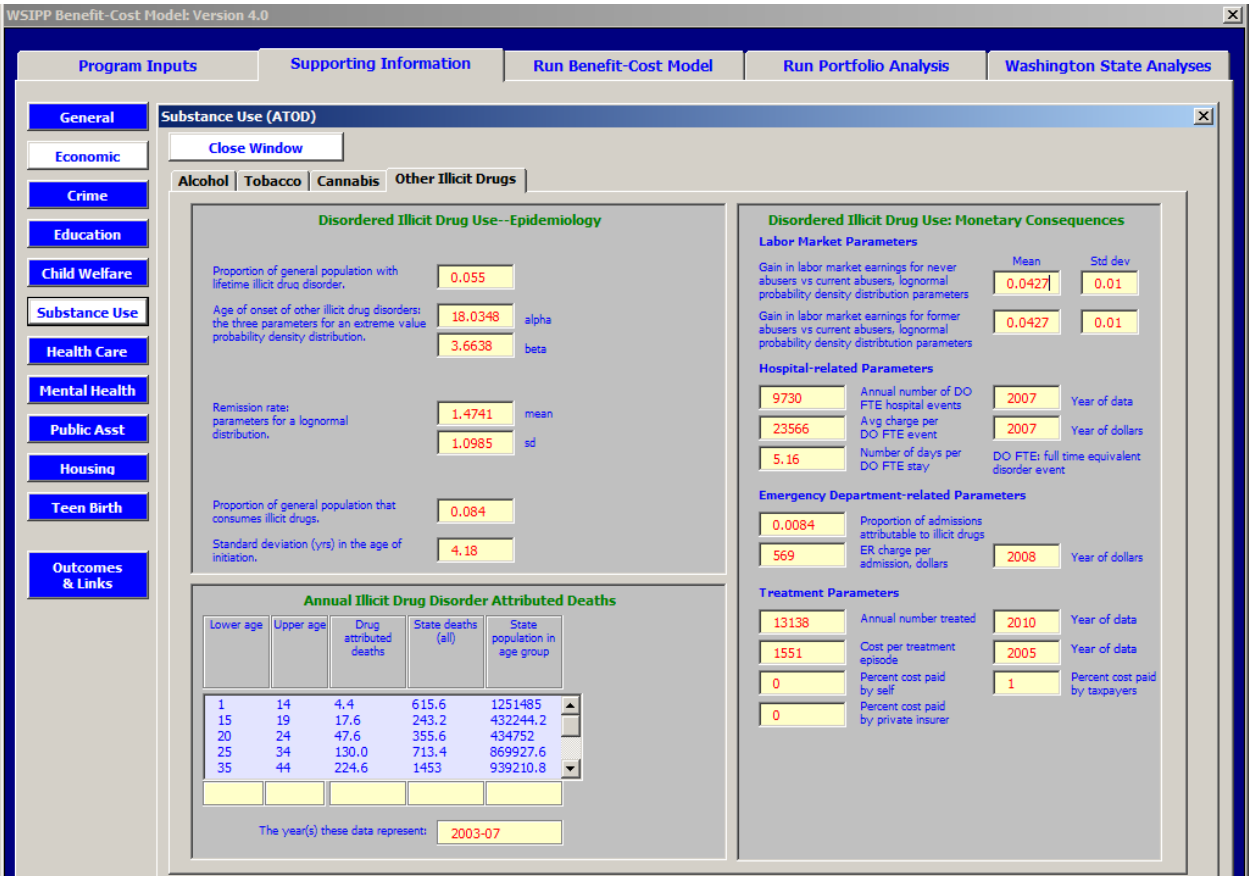
Public Asst
Housing
Teen Birth
Outcomes & Links
Substance Use (ATOD)
Close Window
Alcohol
Tobacco
Cannabis
Other Illicit Drugs
Disordered Cannabis Use--Epidemiology
Proportion of general population with lifetime cannabis disorder.
0.085
Age of onset of cannabis disorders: the three parameters for an extreme value probability density distribution.
18.0348
alpha
3.6638
beta
Remission rate: parameters for a lognormal distribution.
1.7917
mean
1.149
sd
Proportion of general population that consumes cannabis.
0.114
Standard deviation (yrs) in the age of initiation.
3.6
Disordered Cannabis Use: Monetary Consequences
Labor Market Parameters
Mean
Std dev
Gain in labor market earnings for never used cannabis vs current disordered users, lognormal probability density distribution parameters
0.0427
0.01
Gain in labor market earnings for former users vs current disordered users, lognormal probability density distribtution parameters
0.0427
0.01
Treatment Parameters
8524
Annual number treated
2010
Year of data
1551
Cost per treatment episode
2005
Year of data
0
Percent cost paid by self
1
Percent cost paid by taxpayers
0
Percent cost paid by private insurer

Exhibit 43


WSIPP Benefit-Cost Model: Version 4.0
Program Inputs
Supporting Information
Run Benefit-Cost Model
Run Portfolio Analysis
Washington State Analyses
General
Economic
Crime
Education
Child Welfare
Substance Use
Health Care
Mental Health
Public Asst
Housing
Teen Birth
Outcomes & Links
Substance Use (ATOD)
Close Window
Alcohol
Tobacco
Cannabis
Other Illicit Drugs
Disordered Illicit Drug Use--Epidemiology
Proportion of general population with lifetime illicit drug disorder.
0.055
Age of onset of other illicit drug disorders: the three parameters for an extreme value probability density distribution.
18.0348
alpha
3.6638
beta
Remission rate: parameters for a lognormal distribution.
1.4741
mean
1.0985
sd
Proportion of general population that consumes illicit drugs.
0.084
Standard deviation (yrs) in the age of initiation.
4.18
Annual Illicit Drug Disorder Attributed Deaths
Lower age
Upper age
Drug attributed deaths
State deaths (all)
State population in age group
1 14 4.4 615.6 1251485
15 19 17.6 243.2 432244.2
20 24 47.6 355.6 434752
25 34 130.0 713.4 869927.6
35 44 224.6 1453 939210.8
The year(s) these data represent:
2003-07
Disordered Illicit Drug Use: Monetary Consequences
Labor Market Parameters
Mean
Std dev
Gain in labor market earnings for never abusers vs current abusers, lognormal probability density distribution parameters
0.0427
0.01
Gain in labor market earnings for former abusers vs current abusers, lognormal probability density distribtution parameters
0.0427
0.01
Hospital-related Parameters
9730
Annual number of DO FTE hospital events
2007
Year of data
23566
Avg charge per DO FTE event
2007
Year of dollars
5.16
Number of days per DO FTE stay
DO FTE: full time equivalent disorder event
Emergency Department-related Parameters
0.0084
Proportion of admissions attributable to illicit drugs
569
ER charge per admission, dollars
2008
Year of dollars
Treatment Parameters
13138
Annual number treated
2010
Year of data
1551
Cost per treatment episode
2005
Year of data
0
Percent cost paid by self
1
Percent cost paid by taxpayers
0
Percent cost paid by private insurer

4.4b ATOD Epidemiological Parameters: Current Prevalence for Prevention and Intervention Programs

WSIPP's ATOD model begins by analyzing the epidemiology of each ATOD disorder to produce estimates of the current 12-month prevalence of disordered alcohol use, disordered illicit drug use, and regular tobacco smoking. An estimate of the current prevalence of an ATOD disorder is central to the benefit-cost model because it becomes the "base rate" of an ATOD disorder to which program or policy effect sizes are applied to calculate the change in the number of avoided ATOD "units" caused by the program, over the lifetime following treatment.

Four parameters enter the model to enable an estimate of the current prevalence of ATOD, from age 1 to age 100.

- **Lifetime prevalence**: the percentage of the population that has a specific lifetime ATOD disorder.
- **Age of onset**: the age of onset of the specific ATOD disorder.
- **Persistence**: the persistence of the specific ATOD disorder, given onset.
- **Death (survival)**: the probability of death by age, after the age of treatment by a program.

The parameters that enter the model appear on each screen shot; Exhibit 40 also displays the current parameters in WSIPP's model for the first three epidemiological factors, along with sources and notes. The death probability information is described elsewhere in this Chapter.

For each ATOD disorder, the current prevalence of ATOD is estimated with this equation.

$$(4.36) \quad CP_y = \left(\sum_{0=1}^{y} 0_0 \times P_{(y-0+1)} \right) \times LTP \times S_y$$

The current disorder prevalence probability at any year in a person's life, CPy, is computed with information on the age-of-onset probability, O, from prior ages to the current age of the person, times the persistence probability, P, of remaining in the DSM condition at each onset age until the person is the current age, times the lifetime probability of ever having the DSM disorder (or regular tobacco use), LTP, times the probability of survival at each age, Sy, following treatment by a program.

For each ATOD disorder, the exogenous age-of-onset probability distribution for ages 1 to 100, O, is a density distribution and is estimated with information from the sources shown in Exhibit 40. The parameters in Exhibit 45 are the same as those entered by the user on the screen shots in Exhibits 40 through 43.

$$(4.37) \quad 1 = \sum_{y=1}^{100} O_y$$

Also, for each ATOD disorder, the exogenous persistence distribution for ages after onset, P, is computed from the sources shown in Exhibit 45. The persistence distribution describes the probability, on average, of being in the DSM disorder condition each year following onset.

The probability of survival at any given age, Sy, is computed from a national life table on survival, LTS, in the general population. The inputs for the survival table are described in another section of this Benefit-Cost Technical Manual. To compute the current prevalence of a disorder over the entire life course, Sy is normalized to age 1.

$$(4.38) \quad S_y = \frac{LTS_y}{LTS_1}$$

Since the probability of survival depends on the number still living at the treatment age, $tage$, the Sy is normalized to the age of the person being treated in the program being analyzed, since it is assumed that all treatment programs will be for those currently alive at time of treatment.

$$(4.39) \quad S_y = \frac{LTS_y}{LTS_{tage}}$$

Equation 4.36 describes the calculation of current prevalence for general (prevention) populations. For programs treating indicated populations, CPy in equation 4.40 describes the prevalence in all years following treatment.

$$(4.40)\quad CP_y = \frac{\sum_{0=1}^{tage} 0_0 \times P_{(y-0+1)}}{\sum_{0=1}^{tage} 0_0} \times S_y \times SF$$

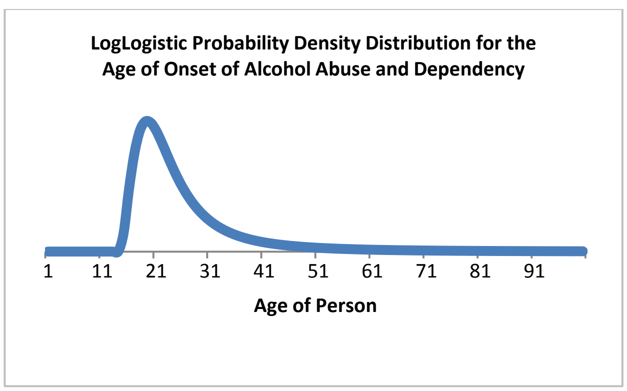
The additional term in equation 4.40 is the reduced chance of survival for someone with an ATOD disorder. We compute an estimate for this as a single parameter with the following equation.

$$(4.41)\quad SF = \frac{\sum_{a=1}^{A}\left(Pop_a \times CP_a \times \dfrac{\frac{(PopD_a - AtodD_a)}{Pop_a}}{\frac{PopD_a}{Pop_a}}\right)}{\sum_{a=1}^{A}(Pop_a \times CP_a)}$$

In this equation 4.41, Pop_a is the total population in a state in each age group, CP_a is the average current ATOD prevalence in each age group, $PopD_a$ is the total number of deaths in a state in each age group, and $AtodD_a$ is the deaths attributable to ATOD in each age group.

Example. We provide an illustrative example of computing CP_y in equation 4.36 for alcohol disorders. Using the results from Hasin et al., we computed a probability density distribution for the age of onset of DSM alcohol disorders. [108] The Hasin study summarizes information from the National Epidemiologic Survey on Alcohol and Related Conditions, a nationally representative sample. We used *@Risk* software to estimate alternative distributions that fit the onset information reported in the Hasin study. We then selected the type of distribution with the best fit where the criterion was the lowest root-mean squared error. For our analysis of the results reported in the Hasin study, we computed a loglogistic density distribution; the estimated parameters are reported in Exhibit 44. The chart below plots the estimated distribution, where the sum of annual probabilities equals 1.0

Exhibit 44



Next, estimates of the persistence of the alcohol disorder, given onset, were computed for alcohol from the study by Lopez-Quintero, et al.[109] The Lopez-Quintero study also used information from the National Epidemiologic Survey on Alcohol and Related Conditions. Again, we used *@Risk* software to model the best fitting cumulative remission curve, and then inverted the result to estimate a persistence curve. A Weibull distribution was the best-fitting curve for this disorder. The resulting estimates measure the probability of remaining in a DSM alcohol disorder in the years following onset. The estimated Weibull parameters are shown in Exhibit 45 and the chart below plots the results.

[108] Hasin, D. S., Stinson, F. S., Ogburn, E., & Grant, B. F. (2007). Prevalence, correlates, disability and comorbidity of DSM-IV alcohol abuse and dependence in the United States: Results from the National Epidemiologic Survey on Alcohol and Related Conditions. *Archives of General Psychiatry, 64*(7), 830-842.

[109] Lopez-Quintero, C., Hasin, D. S., de los Cobos, J. P., Pines, A., Wang, S., Grant, B. F., & Blanco, C. (2011). Probability and predictors of remission from lifetime nicotine, alcohol, cannabis, or cocaine dependence: Results from the National Epidemiologic Survey on Alcohol and Related Conditions. *Addiction, 106*(3), 657-669.

Exhibit 45

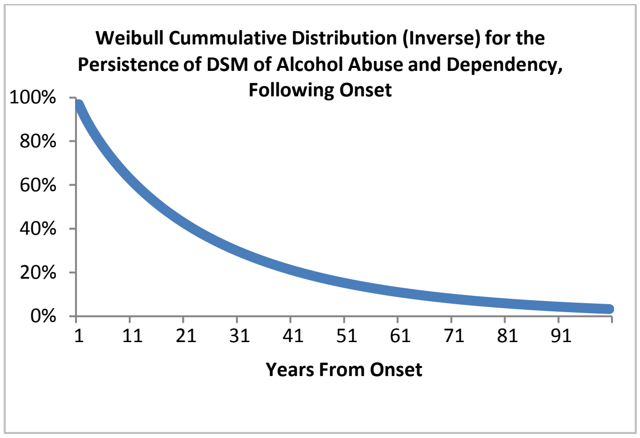
Input Parameters for the Epidemiology of Alcohol Disorders, Illicit Drug Disorders, and Regular Smoking[(1)]

	DSM Alcohol Disorder (a)	DSM Illicit Drug Disorder (Cannabis) (b)	DSM Illicit Drug Disorder (Non Cannabis) (c)	Regular Tobacco Smoking (d)
Percentage of population with lifetime DSM disorder, or regular smoking	24.2%[(2)]	8.5%[(8)]	5.5%[(8)]	39.3%[(11)]
Age of onset				
Type of distribution	Log-logistic[(3)]	Extreme value[(9)]	Extreme value[(9)]	Log-logistic[(12)]
Parameter 1	14.5776	18.0348	18.0348	4.5788
Parameter 2	8.0661	3.6638	3.6638	12.647
Parameter 3	2.05	n/a	n/a	6.8346
Parameter 4	n/a	n/a	n/a	n/a
Remission of DSM disorder, given onset				
Type of distribution	Weibull[(4)]	Lognormal[(4)]	Lognormal[(4)]	Beta-general[(4)]
Parameter 1	.5	1.7917	1.4741	.5
Parameter 2	.86728	1.149	1.0985	.96399
Parameter 3	24.119	n/a	n/a	2.0358
Parameter 4	n/a	n/a	n/a	0
Parameter 5	n/a	n/a	n/a	115.25
Percentage of general population consuming substance	67.2%[(5)]	11.4%[(5)]	8.4%[(5)]	27.8%[(5)]
Age of initiation parameters				
Standard deviation in age of initiation (years)	3.32[(6)]	3.60[(6)]	4.18[(6)]	3.30[(6)]
Effect Size: current DSM prevalence per year of delay	.020[(7)]	.050[(10)]	.024[(10)]	.025[(13)]
Standard Error	.019[(7)]	.011[(10)]	.009[(10)]	.028[(13)]

Notes and sources

1. For benefit-cost modeling, except where noted, alcohol and drug disorders include both DSM categories of abuse and dependence. Tobacco smoking is measured as regular daily smoking. All outcomes are estimated as dichotomous conditions.
2. Vergés, A., Littlefield, A. K., & Sher, K. J. (2001, January 10). Did lifetime rates of alcohol use disorders increase by 67% in ten years? A comparison of NLAES and NESARC. *Journal of Abnormal Psychology*. Advance online publication. This study compares results from the NLAES and NESARC epidemiological surveys. We elected to average the two results for the two national surveys reported in the Vergés study (.1817 and .3028). When the averaged lifetime value is entered into our model, the resulting current prevalence estimate from our model (.077) is nearly identical to the average of the current prevalence estimates, reported by Vergés, from the two national surveys (.079, the average of .0740 and .0846).
3. Hasin, D. S., Stinson, F. S., Ogburn, E, & Grant, B. F. (2007). Prevalence, correlates, disability and comorbidity of DSM-IV alcohol abuse and dependence in the United States: Results from the National Epidemiologic Survey on Alcohol and Related Conditions. *Archives of General Psychiatry, 64*(7), 830-842. From the Figure reported in the paper, we computed a loglogistic probability density distribution for the age of onset of a DSM alcohol disorder, conditional on having a disorder. @Risk software was used to estimate alternative distributions; the distribution with the best fit (criterion: lowest root-mean squared error) was chosen.
4. Lopez-Quintero, C., Hasin, D. S., de los Cobos, J. P., Pines, A., Wang, S., Grant, B. F., & Blanco, C. (2011). Probability and predictors of remission from lifetime nicotine, alcohol, cannabis, or cocaine dependence: Results from the National Epidemiologic Survey on Alcohol and Related Conditions. *Addiction, 106*(3): 657-669. For alcohol and illicit drug disorders and nicotine we fitted cumulative probability distributions to the remission information reported in the study, and then inverted to estimate persistence curves. @Risk software was used to estimate alternative distributions; for each disorder, the distribution with the best fit (criterion: lowest root-mean squared error) was chosen. For alcohol and tobacco, the first parameter shown is a shift parameter. For illicit drug disorders, the non-cannabis estimate is for cocaine, the only non-cannabis illicit drug analyzed in the Lopez-Quintero paper.
5. Analysis of 2009 National Survey on Drug Use and Health. For alcohol, we used the ALCYR variable (used within the past year). We used the MRJYR variable for cannabis (used in past year), the IEMYR variable for illicit drugs other than cannabis (used in past year), and the CIGYR variable (used in past year) for cigarettes.
6. Analysis of 2009 National Survey on Drug Use and Health. For alcohol, we used the IRALCAGE variable (age of initiation, filtered for initiation ages 10 to 30—for analysis of prevention programs, age of initiation beyond 30 is not relevant). We used the IRMJAGE variable (age of cannabis initiation) and IEMAGE (age of initiation of illicit drug use other than cannabis), both filtered for initiation ages 10 to 30—for analysis of prevention programs, age of initiation beyond 25 is not relevant. For cigarettes, we used the IRCIGAGE variable (age of initiation, filtered for initiation ages 7 to 25—for analysis of prevention programs, age of initiation beyond 25 is not relevant).
7. These parameters were computed from an analysis of the research literature examining the probability of the current prevalence of adult DSM alcohol disorder as a function of age of initiation of alcohol consumption. In the analysis, we contributed our own study using the 2009 NSDUH dataset. The units shown are effect sizes on adult DSM alcohol disorders (and standard errors) per year of delay in initiation. The mean effect size was reduced by half to be consistent with WSIPP's adjustments for unobserved selection bias.
8. Compton, W. M., Thomas, Y. F., Stinson, F. S., Grant, B. F. (2007). Prevalence, correlates, disability and comorbidity of DSM-IV drug abuse and dependence in the United States: Results from the National Epidemiologic Survey on Alcohol and Related Conditions. *Archives of General Psychiatry, 64*(5), 566-576. Cannabis disorder prevalence reported in eTable 1. The Compton paper did not report a separate estimate for lifetime prevalence for non-cannabis illicit drugs. We estimated this by applying the data from the 2009 NSDUH, multiplying the current non-cannabis illicit drug prevalence (ABODIEM) by the ratio of lifetime cannabis illicit drug prevalence from the Compton paper to current cannabis prevalence (ABODMRJ) from the NSDUH.
9. *Ibid.* From the Figure reported in the Compton paper, we computed an extreme value probability density distribution for the age of onset of a DSM drug disorder, conditional on having a disorder. @Risk software was used to estimate alternative distributions; the extreme value distribution fit the Compton data well, especially for early ages. The Compton study only reported distributions for all drugs, not separate curves for cannabis and non-cannabis illicit drugs. Hence, we use the same density distribution for both cannabis and other illicit drugs; future research can refine this.
10. These parameters were computed from a multivariate logistic regression analysis of 2009 National Survey on Drug Use and Health data where the probability of the current prevalence of a DSM cannabis use disorder (ABODMRJ) was related to the age of onset of cannabis use (IRMJAGE). Covariates included current age, gender, income, and race. The units shown are effect sizes (and standard errors) per year of delay in initiation. We conducted a similar analysis for DSM non-cannabis illicit drug use disorder. Variables used were ABODIEM, IEMAGE, and current age, gender, income, and race covariates. Mean effect sizes were reduced by half to be consistent with WSIPP's adjustments for unobserved selection bias.
11. Analysis of 2009 National Survey on Drug Use and Health. We used the CIGDLYMO variable (ever smoked cig every day for 30 days) and filtered for ages 26 to 49 to match a post initiation cohort and a post-surgeon general's cohort.
12. Analysis of 2009 National Survey on Drug Use and Health. We used the IRCDUAGE variable (imputation-revised daily cig age of first use). We computed a log-logistic probability density distribution for the age of onset of regular cigarette use. @Risk software was used to estimate alternative distributions; the distribution with the best fit (criterion: lowest root-mean squared error) was chosen.
13. These parameters were computed from an analysis of the research literature examining the probability of the current prevalence of adult regular smoking as a function of age of initiation of smoking. In the analysis, we contributed our own study using the 2009 NSDUH dataset. The units shown are effect sizes on adult regular smoking (and standard errors) per year of delay in initiation. The mean effect size was reduced by half to be consistent with WSIPP's adjustments for unobserved selection bias.

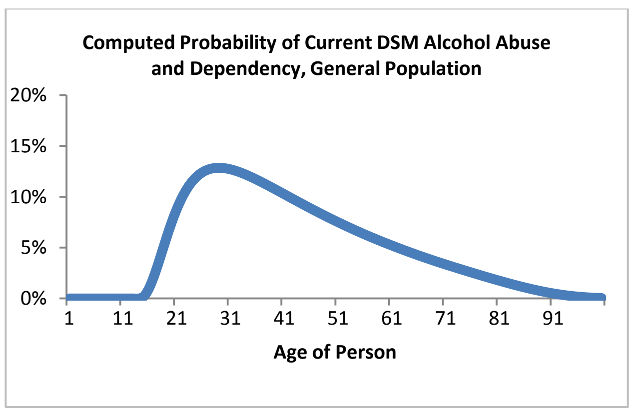
Exhibit 46



The persistence curve, after multiplying by the survival factor, by year, from the 2006 United States life table published by the federal Center for Disease Control, supplies the base rates for intervention programs.

For prevention programs, after applying the estimate of lifetime prevalence of an alcohol disorder, 24.2% with sources shown in Exhibit 45, and after adjusting for survival from the 2006 United States life table published by the federal Centers for Disease Control (and assuming for this example a treatment age of one), the expected current 12-month prevalence of an alcohol disorder during the lifetime of a general population of one-year-olds is computed with equation 4.36 and is plotted on the following chart.

Exhibit 47



The same procedures just described for alcohol disorders are used for disordered illicit drug use (non-cannabis), DSM cannabis use, and regular tobacco smoking, substituting the relevant parameters for the best-fitting distributions as shown in Exhibit 45. As noted, the estimates of the current prevalence of an ATOD is central to the benefit-cost model because it becomes the “base rate” of an ATOD disorder to which program or policy effect sizes are applied to determine the change in the number ATOD “units” caused by the program, over the lifetime following treatment. The general prevalence, shown above, is used for programs targeted at the general population, while the persistence curve (after adjustment for survival probabilities), also shown above, is used as the base rate for programs that treat people with a current ATOD condition.

4.4c ATOD Attributable Deaths

WSIPP’s model computes mortality-related lost earnings, lost household production, and the value of a statistical life. These mortality estimates require estimates of the probability of dying from ATOD. The model inputs for these calculations, for each ATOD disorder, are shown in Exhibits 40 for alcohol, 41 for smoking, and 43 for illicit drugs other than cannabis.

Alcohol. For alcohol-attributable deaths, the data source is the United States Department of Health and Human Services, Centers for Disease Control (CDC). CDC estimates, for each state, the number of deaths attributable to alcohol causes.

The estimates from CDC are available on-line via a software application called *Alcohol-Related Disease Impact (ARDI)*.[110] According to CDC:

> *ARDI either calculates or uses pre-determined estimates of Alcohol-Attributable Fractions (AAFs)—that is, the proportion of deaths from various causes that are due to alcohol. These AAFs are then multiplied by the number of deaths caused by a specific condition (e.g., liver cancer) to obtain the number of alcohol-attributable deaths.*
>
> *A Scientific Work Group, comprised of experts on alcohol and health, was convened to guide development of the ARDI software. The Work Group's tasks included:*
>
> ** Selecting alcohol-related conditions to be included in the application*
> ** Selecting relative risk estimates for the calculation of alcohol-attributable fractions for specific conditions*
> ** Determining prevalence cutpoints for different levels of alcohol use*

The most recent CDC/ARDI estimates for Washington State are the average annual number of alcohol-attributable deaths, by age group shown of Exhibit 40, for the years 2001-05. ARDI estimates deaths related entirely or partially due to particular causes of death. For the deaths partially caused by alcohol, we obtain only the deaths associated with the ARDI "medium and high" alcohol consumption levels, since problem drinking is the focus of our benefit-cost analysis. ARDI also reports deaths due to chronic conditions (e.g. liver cirrhosis, fetal alcohol syndrome, etc.) and acute conditions (e.g. fall injuries, motor vehicle crashes, etc.). Since WSIPP's model focuses on DSM-level alcohol disorders, a portion of the deaths caused by acute conditions could be from alcohol-involved events of someone not with a DSM-level condition. Therefore, for acute deaths, the input screen provides for a single parameter, by age group, to split acute alcohol-related deaths into those where a DSM-alcohol disordered person was involved.

To compute alcohol induced death rates for these age groups, we obtain Washington State population data from the Washington State Office of Financial Management, the state agency charged with compiling official state demographic data. The population estimates are the average Washington population for 2001-05, the same years as the CDC/ARDI death estimates.

Tobacco Smoking. For smoking-attributable deaths, the data source is also the United States Department of Health and Human Services, Center for Disease Control. CDC estimates, for each state, the number of deaths attributable to smoking. The estimates from CDC are available on-line via a software application called *Smoking-Attributable Mortality, Morbidity, and Economic Costs (SAMMEC)*.[111] SAMMEC reports smoking-attributable fractions of deaths for 19 diseases where cigarette smoking is a cause using sex-specific smoking prevalence and relative risk (RR) of death data for current and former smokers aged 35 and older.

Illicit Drugs. For illicit drug deaths, we use death data from the Washington State Vital Statistics dataset for the years 2003 to 2007. For these years, we count the age of all deaths in Washington where ICD-10 death codes match the drug attribution factors contained in Harwood et al.[112] We compute average annual drug attributable deaths in the age groups shown in Exhibit 43.

For each ATOD, the death data are used to compute the probability of dying from ATOD in the general population, by age group.

$$(4.42) \quad AtodD_a = \left((Chronic_a + Acute_a \times AcutePct)/Pop_a\right)/Years_a$$

The probability of dying from a particular ATOD disorder in each age group in the general population, $AtodD_a$, is computed by adding the deaths due to chronic ATOD use, $Chronic_a$, to the proportion of deaths due to acute ATOD use (e.g., motor vehicle crashes due to an alcohol impaired driver), $Acute_a$ times $AcutePct_a$, divided by the total population in the state in each age group, Pop_a. This quotient is divided by the number of years in the age group, $Years_a$, to produce an estimate of the average annual probability of dying from an ATOD disorder.

[110] Centers for Disease Control and Prevention website: https://apps.nccd.cdc.gov/ardi/HomePage.aspx
[111] Centers for Disease Control and Prevention website: http://apps.nccd.cdc.gov/sammec/
[112] Office of National Drug Control Policy. (2004).*The economic costs of drug abuse in the United States, 1992-2002* (Publication No. 207303). Washington, DC: Executive Office of the President, Author, Table B-10.

4.4d Linkages: ATOD and Other Outcomes

WSIPP's benefit-cost model monetizes improvements in ATOD outcomes, in part, with linkages between each ATOD and other outcomes to which a monetary value can be estimated. The parameters for these linkages are obtained by a meta-analytic review of relevant research literature. For example, we estimate the relationship between disordered alcohol use and labor market earnings by meta-analyzing the most credible studies that have addressed this topic. The meta-analytic process provides both an expected value effect given the weight of the evidence, and an estimate of the error of the estimated effect. Both of these parameters are entered into the benefit-cost model and used when performing a Monte Carlo simulation. The linkages in the current WSIPP model are listed in Chapter 5.

4.4e Human Capital Outcomes Affecting Labor Market Earnings via ATOD-Caused Morbidity and Mortality

The WSIPP model computes lost labor market earnings, as a result of ATOD morbidity and mortality, when there is evidence that the linkage is causal. The procedures begin by estimating the labor market earnings of an average person with a current ATOD disorder. As described in Chapter 4.1, WSIPP's model uses national earnings data from the U.S. Census Bureau's Current Population Survey. The CPS data used in this analysis represent average earnings of all people, both workers and non-workers at each age.

For each person at each age, total CPS earnings can be viewed as a weighted sum of people who have never had an ATOD disorder, plus those that are currently disordered, plus those that were formerly disordered, but do not currently have a disorder. From the CPS data on total earnings for all people, the earnings of individuals with a current ATOD condition, at each age, y, is computed with this equation:

$$(4.43)\quad EarnC_y = \frac{EarnAll_y \times (1+EarnEscAll)^{y-tage} \times EarnBenAll \times (1+EarnBenEscAll)^{y-tage} \times \left(IPD_{base}/IPD_{cps}\right)}{\left((1+EarnGN)\times\left(1-\left(CP_y+\left(\sum_{o=1}^{y}(O_o\times LTP)-CP_y\right)\right)\right)+(1+EarnGF)\times\left(\sum_{o=1}^{y}(O_o\times LTP)-CP_y\right)+CP_y\right)}$$

The numerator in the above equation includes the CPS earnings data for all people, *EarnAll*, with adjustments for real earnings growth, *EarnEscAll*, earnings-related benefits, *EarnBenAll*, growth rates in earnings benefits, *EarnBenEscAll*, and an adjustment to denominate the year of the CPS earnings data, *IPDcps*, with the year chosen for the overall analysis, *IPDbase*. These variables are described in Chapter 4.1.

The denominator uses the epidemiological variables described above: age of onset probabilities, Oy, lifetime prevalence rates, LTP, and current 12-month prevalence rates, CPy, at each age.

The denominator also includes two variables on the earnings gain of never-disordered people compared to currently disordered people, $EarnGN$, and the earnings gain of formerly disordered people compared to currently disordered people, $EarnGF$. These two central relationships measure the effect of ATOD on labor market success (as measured by earnings); each are listed in the three input screens. These relationships are derived from meta-analytic reviews of the relevant research literature.

For ATOD disorders (including regular smoking), we meta-analyze two sets of research studies: one set examines the relationship between ATOD disorders and employment rates, and the second examines the relationship between ATOD disorders and earnings, conditional on being employed. Exhibit 68 in Chapter 5 displays the results of our meta-analysis of these two bodies of research for each ATOD disorder. Our meta-analytic procedures are described in Chapter 2.

For each ATOD disorder, from these two findings—the effect of ATOD disorders on employment, and the effect of ATOD disorders on the earnings of those employed—we then combined the results to estimate the relationship between an ATOD disorder and average earnings of all people (workers and non-workers combined). To do this, we used the effect sizes and standard errors from the meta-analyses on employment and earnings of workers. We used data from the 2009 CPS earnings for average earnings of those with earnings and the standard deviation in those earnings and the proportion of the CPS sample with earnings. We then computed the mean change in earnings for all people by computing the change in the probability of earnings and the drop in earnings for those with earnings. The ratio of total earnings (for both workers and non-workers) for non-disordered individuals to ATOD disordered individuals was then computed.

This mean effect, however, is estimated with error because of the standard errors in the meta-analytic results reported above. Therefore, we used @RISK distribution fitting software to model the joint effects of an alcohol disorder on the mean ratio, given the errors in the two key effect size parameters. The distribution with the best fit (criterion: lowest root-mean squared error) was chosen; for all four disorders, a lognormal distribution was best. Therefore, the two lognormal distribution parameters are entered in the model, as shown in Exhibits 40, 41, 42, and 43. Since the body of evidence we reviewed in the meta-analysis did not allow separation of the effects into (1) never disordered people vs. currently disordered people and (2) formerly disordered people vs. currently disordered people, we enter the same lognormal parameters for both the *EarnGN* and the *EarnGF* variables. The sole exception was for smoking, as shown in Exhibit 41. Here, the evidence from our review of the literature indicated that former smokers suffer no earnings penalty relative to never smokers. Therefore, we set that parameter to zero.

The present value of the change in morbidity-related earnings for a prevention program that produces a change in the probability of a current ATOD is given by:

$$(4.44)\ \ PV\Delta Earn = \sum_{y=tage}^{65} \frac{\left(\Delta ATOD_y \times \left(1-\sum_{o=1}^{y} O_o\right) \times EarnGN \times EarnC_y\right) + \left(\Delta ATOD_y \times \left(1-\left(1-\sum_{o=1}^{y} O_o\right)\right) \times EarnGF \times EarnC_y\right)}{(1+dis)^{(y-tage+1)}}$$

Where *ΔATODy* is the change in ATOD probability; *O* are the annual onset probabilities; *EarnGN* is the earnings gain of never-disordered people compared to currently disordered people; *EarnGF* is the earnings gain of formerly disordered people compared to currently disordered people; *dis* is the discount rate; and *tage* is the treatment age of the person in the program. Since a prevention program may serve people without a disorder and with a disorder, the above model weights that probability by the age of onset probabilities.

The present value of the change in the morbidity-related earnings for a treatment program that produces a change in the probability of people with a current ATOD disorder is given by:

$$(4.45)\ \ PV\Delta Earn = \sum_{y=tage}^{65} \frac{\left(\Delta ATOD_y \times EarnGF \times EarnC_y\right)}{(1+dis)^{(y-tage+1)}}$$

This model for a treatment program is simpler than that for a prevention program because, by definition, a treatment program only attempts to turn currently disordered ATOD people into former ATOD people.

$$(4.46)\quad PVL{:}\,P_{mort} = \sum_{a=A}^{100} \frac{PE_a \times R_a \times \sum_{y=a}^{100}\left(LC_y \times (1+LGN)\right) \times DeathPrP_a + PE_a \times (1-R_a) \times \sum_{y=a}^{100}\left(LC_y \times (1+LGF)\right) \times DeathPrP_a}{(1+Dis)^a}$$

For labor market morbidity-related benefits for treatment programs, the labor market benefits of ATOD reductions are computed with this equation:

$$(4.47)\ \ PVL{:}\,T_{morb} = \sum_{a=A}^{100} \frac{LC_a \times LGF \times PE_a}{(1+Dis)^a}$$

4.4f Medical Costs, Treatment Costs, and Other Costs From ATOD

The WSIPP model computes estimates of changes in avoidable hospital and other medical costs as a result of ATOD morbidity and mortality, including estimates of avoidable treatment costs for alcohol and drug disorders, and for avoidable traffic crash costs for alcohol.

Hospital-Related Parameters. The costs of hospital charges attributable to alcohol, illicit drugs, and smoking, are computed with information from the Washington State Comprehensive Hospital Abstract Reporting System (CHARS) system. CHARS contains hospital inpatient discharge information (derived from billing systems). We use 2007 CHARS data in this analysis. CHARS collects information on billed charges of patients, as well as the codes for their diagnoses. We apply the attributable fraction information, described in 4.4e of this Chapter, to the CHARS data to estimate the number of attributable full time equivalent hospital events by ATOD, *FTEHospitalEvents*, as well as the average billed charge per event, *HospCostEvent*, and the average number of days on an inpatient stay, given a stay. These parameters are shown in Exhibits 40, 41, and 43, for alcohol, tobacco, and illicit drugs, respectively. We also apply a hospital cost-to-charge ratio as described in Chapter 4.9.

From these inputs, we then compute an upper bound number of events per DSM disorder under the assumption that all classified hospital events stemmed from individuals currently diagnosed with a DSM ATOD disorder (or current regular smokers for tobacco-related hospital events). A lower bound is calculated assuming that all hospital events stemmed simply from the general use of ATOD, whether or not the use was from DSM disordered populations.

$$(4.48)\quad ExpHospEventsUpperBound = \frac{FTEHospitalEvents}{\frac{\sum_{y=1}^{100} CP_y \times Pop_y}{\sum_{y-1}^{100} Pop_y}}$$

$$(4.49)\quad ExpHospEventsLowerBound = \frac{FTEHospitalEvents}{CurrentUse\% \ \times \sum_{y=1}^{100} Pop_y}$$

$$(4.50)\quad ExpHosp\$ = \frac{ExpHospEventUpperBound + ExpHospEventLowerBound}{2} \times HospCostEvent \ \times CostRatio$$

In computations, the upper bounds and lower bounds form a triangular probability density distribution (with the mean taken as the mode). In Monte Carlo simulation, a random draw is taken from this probability distribution in order to attribute a hospital charge to a disordered DSM ATOD event.

Thus far, the calculations only cover hospitalization costs. Following the work of Rosen et al., we also make an adjustment to include pharmacological drugs and other medical non-durable costs.[113] To do this, we multiply the expected hospitalization costs, *ExpHosp$*, by the sum of drug and other non-durable medical costs and total hospital care costs, divided by total hospital care costs. The data for these two cost categories for Washington are the aggregate totals entered in Exhibit 57.

Emergency Department Parameters. Emergency Department parameters are shown in Exhibits 40 for alcohol, 41 for tobacco, and 43 for illicit drugs other than cannabis. The model uses a similar approach to that described for hospital events and costs. The model uses an estimate of the probability that an emergency room event is attributable to an alcohol, tobacco, or illicit drug related event. McDonald et al. (2004) estimate 7.9% of emergency room visits are alcohol related; Bernstein (2009) estimates 4.9% of emergency room visits are tobacco induced; and data from the Drug Abuse Warning Network provide a national estimate of drug-related emergency department visits of 0.84%.[114]

The total number of emergency department visits in Washington during 2008 is entered in Exhibit 57. These data come from a report by the Washington State Hospital Association.[115] We then apply the attributable fractions just described; for example, for alcohol, we apply the 7.9% causation factor to determine the number of alcohol-related emergency room visits. As with hospital events, we compute upper and lower bound by dividing by the current annual prevalence of DSM disorders in the general population (upper bound) or the current level of use (not just DSM disorders) in the general population (lower bound). We then apply a cost per emergency department event, *EDCostEvent,* and an emergency department cost-to-charge ratio. The cost per emergency department is taken as the median cost from the Medical Expenditure Panel Survey (MEPS) of the U.S. Department of Health & Human Services.[116] In computations, the upper bounds and lower bounds form a triangular probability density distribution (with the mean taken as the mode). In Monte Carlo simulation, a random draw is taken from this probability distribution in order to attribute a emergency department charge to a disordered DSM ATOD event.

$$(4.51)\quad ExpEDEventsUpperBound = \frac{TotalEDVists \times CausationFraction}{\frac{\sum_{y=1}^{100} CP_y \times Pop_y}{\sum_{y-1}^{100} Pop_y}}$$

$$(4.52)\quad ExpEDEventsLowerBound = \frac{TotalEDVists \times CausationFraction}{CurrentUse\% \ \times \sum_{y=1}^{100} Pop_y}$$

$$(4.53)\quad ExpED\$ = \frac{ExpEDEventsUpperBound + ExpEDEventsLowerBound}{2} \times EDCostEvent \ \times CostRatio$$

[113] Rosen et al. (2008).

[114] McDonald, A. J., Wang, N., & Camargo Jr., C. A. (2004). US emergency department visits for alcohol-related diseases and injuries between 1992 and 2000. *Archives of Internal Medicine, 164*(5), 531-537.; Bernstein, S. L. (2009). The clinical impact of health behaviors on emergency department visits. *Academic Emergency Medicine, 16*(11), 1054-1059.; Center for Behavioral Health Statistics and Quality. (2011). *Drug abuse warning network, 2008: National estimates of drug-related emergency department visits* (HHS Publication No. SMA 11-4618). Rockville, MD: United States Department of Health and Human Services, Substance Abuse and Mental Health Services Administration, Author.

[115] Washington State Hospital Association. (2010). *Emergency room use* (Developed by WSHA's Health Information Program). Seattle, WA: Author. The Association reports 18 months of data with a total of 2,631,071 visits during the 18 month period from January 2008 to June 2009. We converted this number to an annual estimate for 2008 by multiply by 12/18.

[116] Agency for Healthcare Research and Quality. (2011). Emergency room services-mean and median expenses per person with expense and distribution of expenses by source of payment: United States, 2008 (Medical Expenditure Panel Survey Household Component Data, Table 6). Retrieved June 30, 2011.

Treatment Parameters. For the cost of admissions for treatment, we undertook an analysis identical to those just described. We obtain the total number of publicly funded treatment events in Washington for alcohol, cannabis, and illicit drugs from the Treatment Episode Data Set (TEDS) of the U.S. Substance Abuse & Mental Health Services Administration. These data are entered in Exhibits 40, 42, and 43. The public cost per treatment is taken from a study of Washington substance abuse treatment by Wickizer in 2007.[117] We then use the same computational process just described.

$$(4.54)\quad ExpTreatmentEventsUpperBound = \frac{TotalTreatmentEvents}{\frac{\sum_{y=1}^{100} CP_y \times Pop_y}{\sum_{y-1}^{100} Pop_y}}$$

$$(4.55)\quad ExpTreatmentEventsLowerBound = \frac{TotalTreatmentEvents}{CurrentUse\% \times \sum_{y=1}^{100} Pop_y}$$

$$(4.56)\quad ExpTreatment\$ = \frac{ExpTreatmentEventsUpperBound + ExpTreatmentEventsLowerBound}{2} \times TreatmentCostEvent$$

Traffic Crash Parameters. We model alcohol-involved property crash costs with a similar set of procedures. We estimate the annual number of alcohol involved traffic crashes in Washington by obtaining the total number of officer reported traffic collision in Washington in 2009 (102,859).[118] To estimate the proportion of all crashes that are reported by police out of total crashes, we use national estimates produced by Blincoe et al. (2002).[119] Data from Table 3 of Blincoe provide an estimate that 56.7% of all crashes are reported by police. Thus, an estimate of total crashes in Washington in 2009 is 181,390. To this we apply the alcohol induced causation factor (8.5%) derived from national information also provided in Blincoe et al. (2002), along with the average property crash cost, also from Blincoe et al. (2002) of $1,891 in 2000 dollars.

$$(4.57)\quad ExpTrafficCollisionsUpperBound = \frac{TotalTrafficCollisions \times CausationFraction}{\frac{\sum_{y=1}^{100} CP_y \times Pop_y}{\sum_{y-1}^{100} Pop_y}}$$

$$(4.58)\quad ExpTrafficCollisionsLowerBound = \frac{TotalTrafficCollisions \times CausationFraction}{CurrentUse\% \times \sum_{y=1}^{100} Pop_y}$$

$$(4.59)\quad ExpTrafficCollison\$ = \frac{ExpTrafficCollisionsUpperBound + ExpTrafficCollisionsLowerBound}{2} \times TrafficCostEvent$$

4.4g Age of Initiation of ATOD

As described above, we estimate the costs of disordered use of alcohol, cannabis, other illicit drugs, and regular smoking. These costs are tied to the prevalence of consumption patterns. Many of the ATOD measures used in evaluations of prevention and early intervention programs, however, are measures of the age at initiation of alcohol. Therefore, in order to estimate the long-term costs of disordered ATOD, it is necessary to determine whether there is a causal link between the delay in the age at initiation and the ultimate disordered use of ATOD. For each ATOD disorder, we review the literature and contribute original analysis using NSDUH data. Our estimates and sources for these age of initiation parameters are described in Exhibit 45.

[117] Wickizer, T. M. (2007). *The economic costs of drug and alcohol abuse in Washington State, 2005*. Olympia: Washington State Department of Social and Health Services, Division of Alcohol and Substance Abuse.
[118] Washington State Department of Transportation. (n.d.). *2009 Washington State collision data summary*. Olympia, WA: Author. Retrieved June 30, 2011 from http://www.wsdot.wa.gov/mapsdata/collision/pdf/Washington_State_Collision_Data_Summary_2009.pdf
[119] Blincoe, L. J., Seay, A. G., Zaloshnja, E., Miller, T. R., Romano, E. O., Luchter, S., & Spicer, R. S. (2002). *The economic impact of motor vehicle crashes 2000*. Washington, DC: United States Department of Transportation, National Highway Traffic Safety Administration.

4.5 Valuation of Teen Birth Outcomes

In this benefit-cost model, the implications of a teen birth are expressed in terms of the birth's effect on the other outcomes we evaluated. That is, we evaluate the economic consequences of a teen birth based on its relationship to subsequent high school graduation rates, public assistance usage, crime rates, child abuse and neglect cases, K–12 grade repetition, and other outcomes. We evaluate these effects for both the teen mother and the child born to the teen mother. We estimate these effects for births to teens under the age of 18.[120] The results from our meta-analyses of the research literature are shown in Chapter 5.

4.6 Valuation of Public Assistance Outcomes

A portion of public assistance costs are treated as transfer payments in the benefit-cost model. If a program has an effect on public assistance use, then there is a redistribution of costs between program recipients and taxpayers. For example, if an early childhood education program lowers the use of public assistance, then the reduced public assistance payments are a benefit to taxpayers, but a loss of income to the family in the early childhood assistance program. The only net real cost difference in this transfer is the effect that a change in public assistance caseloads has on costs related to the administration of the public assistance programs.

In addition, we estimate the additional costs of the Temporary Assistance for Needy Families (TANF) program on a per-participant basis. Using state data reported to the federal Administration on Children and Families, we compute the total non-assistance TANF expenditures, net of child care costs, as a proportion of total assistance expenditures.[121] We also use this data source to compute the proportion of total TANF expenditures that come from state versus federal sources.

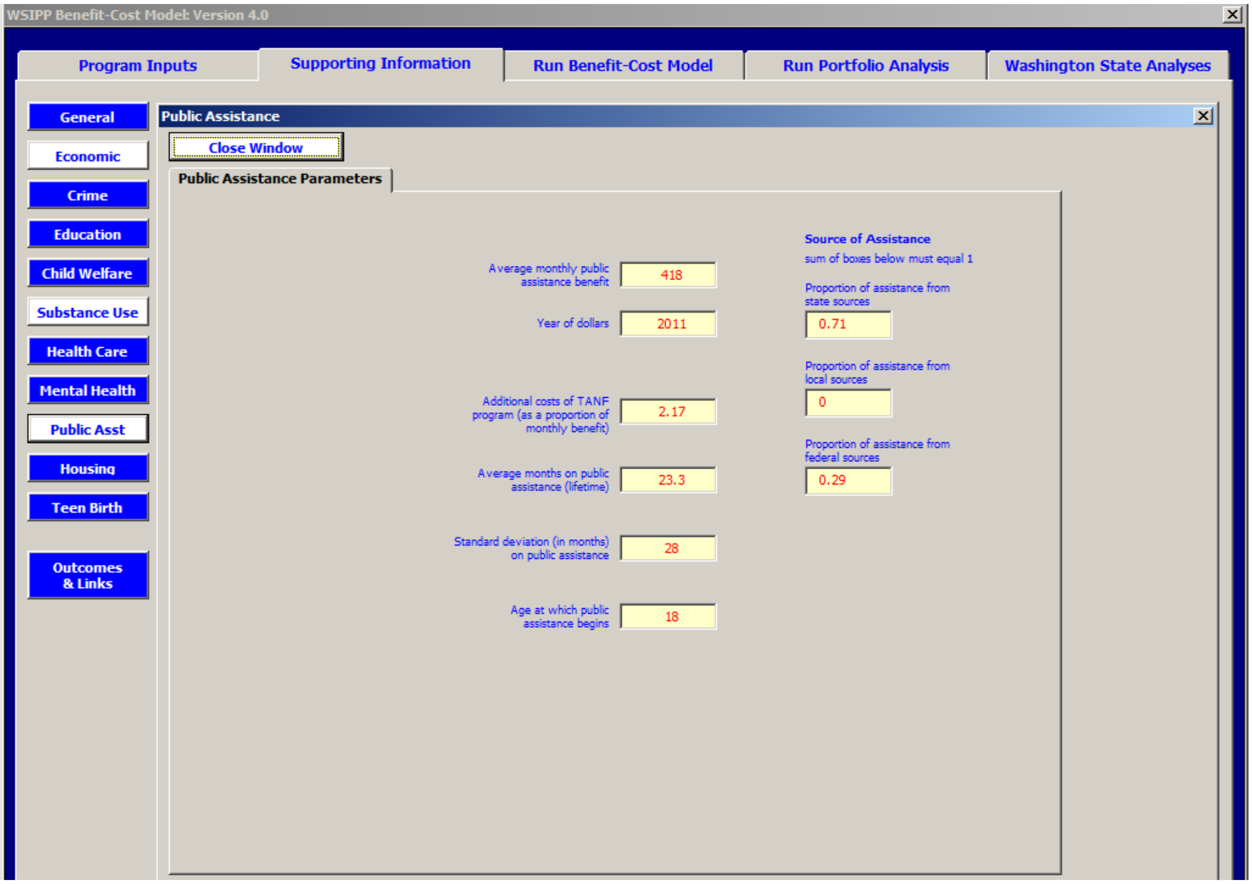
Exhibit 48 displays the input screen for this area. Program effects are measured, most often, as a continuous measure of the number of months on public assistance. Therefore, in addition to additional TANF program costs and the proportion of state and federal TANF expenditures, we also enter information on Washington State public assistance caseloads including the mean number of months on public assistance for those on the caseload, the standard deviation in the number of months, the average monthly assistance amount, a percentage for agency administrative costs and, for modeling purposes, the age at which public assistance receipt begins.[122]

[120] In using the age 18 as a cut-off, we follow the same approach found in Hoffman, S. D. & Maynard, R. A. (Eds.). (2008). *Kids having kids: Economic costs & social consequences of teen pregnancy* (2nd edition). Washington, DC: Urban Institute Press.

[121] Retrieved August 5, 2013 from http://www.acf.hhs.gov/sites/default/files/ofa/2011_tanf_data_with_states.pdf.

[122] The average number of months adults receive TANF in Washington was obtained from: Economic Services Administration. (2012, December). *ESA briefing book: State fiscal year 2012. A reference for programs, caseloads, and expenditures*. Olympia: Washington State Department of Social and Health Services. Retrieved August 5, 2013 from http://www.dshs.wa.gov/pdf/main/briefingbook/2012ESA_Briefing_Book_Full.pdf. The standard deviation was calculated based on a population of female TANF recipients who had participated in an Institute survey in 2008; see: Miller, M. (2011). *Depression in Washington's female TANF population: Prevalence, DSHS screening, and treatment*. (Document No. 11-02-3401). Olympia: Washington State Institute for Public Policy.

Exhibit 48


WSIPP Benefit-Cost Model: Version 4.0
Program Inputs
Supporting Information
Run Benefit-Cost Model
Run Portfolio Analysis
Washington State Analyses
General
Economic
Crime
Education
Child Welfare
Substance Use
Health Care
Mental Health
Public Asst
Housing
Teen Birth
Outcomes & Links
Public Assistance
Close Window
Public Assistance Parameters
Average monthly public assistance benefit
418
Year of dollars
2011
Additional costs of TANF program (as a proportion of monthly benefit)
2.17
Average months on public assistance (lifetime)
23.3
Standard deviation (in months) on public assistance
28
Age at which public assistance begins
18
Source of Assistance
sum of boxes below must equal 1
Proportion of assistance from state sources
0.71
Proportion of assistance from local sources
0
Proportion of assistance from federal sources
0.29

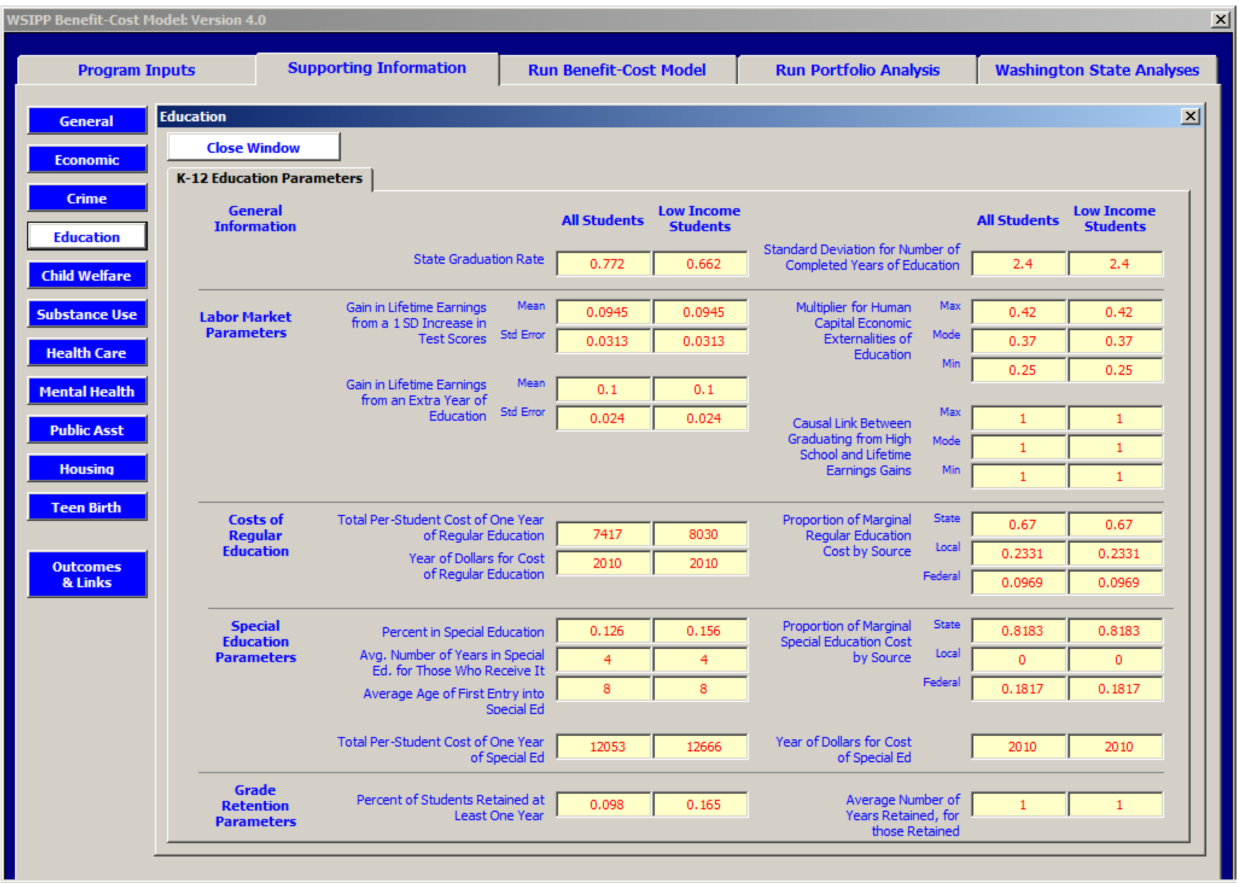
4.7 Valuation of K–12 Education Outcomes

In valuing most K–12 education outcomes (i.e., standardized test scores, high school graduation, and years of education), we use a human capital approach, as described in Chapter 4.1. This section of the Chapter describes the inputs to define baseline parameters of those analyses, as well as the methods for valuing the outcomes of K–12 special education and grade retention.

4.7a Input Screens for Education Parameters

Evaluations of education and other programs or policies often assess outcome measures such as student test scores, years of education, graduation rates, special education, or grade retention. WSIPP's benefit-cost model includes a number of education-related parameters to provide estimates of the benefits of these education outcomes. The inputs are entered into the model on a single user screen shown in Exhibit 49.

Exhibit 49



The Relationship Between Gains in Student Test Scores and Labor Market Earnings. To evaluate outcomes that measure gains in student standardized test scores, the model contains a parameter and standard error to measure how a one standard deviation gain in test scores relates to a percentage increase in labor market earnings. The standard error for this input is used in Monte Carlo simulations (see Chapter 6). For these two parameters, we use regression results from Hall & Farkas (2011).[123] They estimate multi-level models of cognitive ability (measured with standardized test scores) and attitudinal/behavioral traits (sometimes called non-cognitive skills) on log wages with data from the National Longitudinal Survey of Youth (NLSY79). We compute weighted averages from their results for males and females, and for white, black, and Latino populations. We use Monte Carlo simulation to estimate a standard error from their constant and slope parameters. Their results are useful for the benefit-cost model because the cognitive ability scale they create measures several areas (word knowledge, paragraph comprehension, math knowledge, and arithmetic reasoning) found in the program evaluation literature. The results are in line, though slightly lower, than those found in other studies.[124] We enter the same parameter for all students and for low-income students, because we have not found separate estimates for low-income populations.

The Relationship Between Gains in Years of Education Completed and Labor Market Earnings. To evaluate outcomes that measure gains in educational attainment, the model contains a parameter and standard error to measure how an extra year of education relates to a percentage increase in labor market earnings. This topic has been one of long-standing interest among economists, and many reviews of the literature are available. For example, Psacharopoulos and Patrinos review many studies from many countries and conclude that "the average rate of return to another year of schooling is 10 percent."[125] Newer estimates employ more rigorous econometric methods to estimate causal effects and have found that returns are usually slightly higher than previous estimates. Heckman et al., however, have found that the estimates vary considerably depending on when the extra year of education occurs. If the extra year leads to high school graduation, for example, the returns are considerably higher than the single point estimates for extra years of college education.[126] For this reason, we estimate the gains from graduating high school separately, as described below. In our own review of the research, we found a median 10% increase in labor market earnings per additional year of education completed (with a standard error of .02).[127] For consistency purposes, the study by Hall and Farkas (2011) that we use for the effect of student test scores on labor market earnings, found a 9.5% rate of return for an extra year of education—a rate very similar to the 10% rate we use in our model. We set the same parameter for all students and for low-income students, because our review of the research does not provide separate estimates for low-income populations.

The Standard Deviation in the Number of Completed Years of K–20 education. We use microdata from the March Current Population Survey to calculate the standard deviation in the number of years of education attained by adults age 25 or older in the United States who completed at least 7th grade.

The High School Graduation Rate. The model contains a user-supplied parameter of the high school graduation rate. WSIPP's entry is Washington State's current on-time graduation rate as published by the Office of Superintendent of Public Instruction (OSPI).[128] The on-time rate is defined as the percentage of public school students who graduate from high school within four years. We record OSPI's rate for all students and for low-income students.[129]

[123] Hall, M. & Farkas, G. (2011). Adolescent Cognitive Skills, Attitudinal/Behavioral Traits and Career Wages. *Social Forces 89*(4), 1261-1285.

[124] See Hanushek, E. A. (2009) The economic value of education and cognitive skills. In Sykes, G., Schneider, B., & Plank D. (Eds.), *Handbook of education policy research* (pp. 39-56). New York: Routledge.

[125] Psacharopoulos, G. & Patrinos, H. A. (2004). Returns to investment in education: A further update. *Education Economics, 12*(2), 111-134.

[126] Heckman, J., Lochner, P., & Todd, P. (2008). Earnings functions and rates of return. *Journal of Human Capital, 2*(1), 1-31.

[127] We estimated this figure by taking the median of the estimates in Angrist, J. D. & Krueger, A. B. (1991). Does compulsory school attendance affect schooling and earnings? *Quarterly Journal of Economics, 106*(4), 979-1014; Conneely, K. & Uusitalo, R. (1997). *Estimating heterogeneous treatment effects in the Becker schooling model*. Unpublished discussion paper, Industrial Relations Section, Princeton, NJ: Princeton University; Harmon, C. & Walker, I. (1995). Estimates of the economic return to schooling for the United Kingdom. *American Economic Review, 85*(5), 1278-1286; Hausman, J. A. & Taylor, W. E. (1981). Panel data and unobservable individual effects. *Econometrica, 49*(6),1377-1398; Kane, T. & Rouse, C. E. (1993). *Labor market returns to two- and four-year colleges: Is a credit a credit and do degrees matter?* (NBER Working Paper No. 4268). Cambridge, MA: National Bureau of Economic Research; J. Maluccio. (1997). *Endogeneity of schooling in the wage function*. Unpublished manuscript, Department of Economics, Yale University; Staiger, D. & Stock, J. H. (1997). Instrumental variables regression with weak instruments. *Econometrica, 65*(3), 557-586. These studies are summarized in Card, D. (1999). The causal effect of education on earnings. In Ashenfelter E. & Card, D. (Eds.), *Handbook of Labor Economics* (vol. 3, part A, pp. 1801-1863). Atlanta, GA: Elsevier.

[128] Office of Superintendent of Public Instruction. (2013). *Graduation and dropout statistics for Washington in 2011-12*. Olympia, WA: Author. Retrieved August 12, 2013 from http://www.k12.wa.us/dataadmin/pubdocs/GradDropout/11-12/GradandDropOutStats2011-12.pdf

[129] Low-income students are those eligible for free or reduced-price meals in the National School Lunch Program and School Breakfast Program. Students in households with income up to 130% of federal poverty guidelines are eligible for free meals, and those in households up to 185% of federal poverty guidelines are eligible for reduced-price meals. For more information visit: http://www.k12.wa.us/ChildNutrition/Programs/NSLBP/default.aspx

The relationship between high school graduation and labor market earnings. The model contains a user-supplied parameter to measure the degree of causation between the observed earnings differentials (in the Current Population Survey, described in Chapter 4.1) for high school graduates and non-graduates. A parameter value of less than one indicates that some of the observed difference is not due, causally, to obtaining a high school diploma but, instead, to other unobserved factors such as motivation or labor market signaling. A zero value implies no causal relationship between any observed differences in earnings, while a value of one indicates that all of the difference in observed earnings is due to the possession of a high school diploma. This parameter is modeled as a triangular probability density distribution. The input screen allows the user to enter a maximum value for this parameter (a value less than or equal to one), a modal value (a value of greater than or equal to zero or less than or equal to one), and a minimum value (a value greater than or equal to zero). WSIPP's entries for the maximum, mode, and minimum are set to one. We base these estimates on the work of Rouse[130] and Heckman et al.[131] Heckman finds very large internal rates of return for high school graduation for both white and black men (they did not study women)—approximately 50%. This estimate is in line with an internal rate of return of the difference in earnings observed in the CPS sample (used in this study), given a reasonable up-front level of what Heckman calls "psychic costs" of youths staying in school instead of dropping out.

The K–12 Resource Outcomes. The model can also calculate the value of two other K–12 educational outcomes: years of special education and grade retention. In the user input table shown in Exhibit 49, information is entered for the cost of a year of special education, the year in which the special education costs per year are denominated, and the estimated average number of years that special education is used, conditional on entering special education. The user also enters the age when special education is assumed to first be used. The model also requires an estimate of the marginal cost of a year of K–12 education and the year in which these dollars are denominated.[132]

The Percentage of Students Retained in a Grade Level. The model contains a user-supplied parameter of the percentage of students held back at least one year of school in K–12. WSIPP's entry is based on 2009 national rates (9.8% of all students and 16.5% of low-income students) calculated by the U.S. Department of Education.[133] These rates have dropped in recent years; in 1995, 16% of U.S. students had been retained in a grade level.[134]

The Percentage of Students in Special Education. The model contains a user-supplied parameter of the percentage of students in special education. WSIPP's entry is the percentage of Washington State students in special education in 2009-10 (12.6%).[135] This rate is not calculated for low-income students in Washington; for this group, we use national estimates of the prevalence of learning disabilities by income level from Planty et al.,[136] to adjust Washington's special education rate to 15.6% for low-income students.[137]

Multiplier for Human Capital Economic Externalities of Education. The model contains user-supplied low, modal, and high estimates for the ratio of external economic benefits to private economic benefits of education. There is a fairly large literature on this topic, summarized in a chapter by McMahon in Brewer.[138] The low value we use is the estimate contained in Acemoglu & Angrist (2000).[139] The modal value is the estimate used in Belfield, Hollands, and Levin

[130] Rouse, C. E. (2007). Consequences for the labor market. In Belfield, C. & Levin, H. M. (Eds.), *The price we pay: Economic and social consequences of inadequate education* (pp. 99-124). Washington, DC: Brookings Institution Press.
[131] Heckman et al. (2008).
[132] The total cost for one year of special education represents the cost of one year of regular education per student from all sources (state, federal, and local) plus the state allocation for each special education student. The cost of regular education estimate is from: Office of Superintendent of Public Instruction. (2010). *Financial reporting summary: School district and educational service district* (Fiscal Year September 1, 2008 – August 31, 2009). Olympia, WA: Author, Table 4. Retrieved June 30, 2011 from http://www.k12.wa.us/safs/PUB/FIN/0809/0809FinSumweb-7.20.2010.pdf; the special education allocation estimate is from: Office of Superintendent of Public Instruction. (2011). *OSPI apportionment report for May 31, 2011* (p. 10, report 1220). Retrieved June 30, 2011 from http://www.k12.wa.us/safs/month.asp. The average number of years of special education and the average age of first entry in special education are WSIPP estimates.
[133] Planty et al. (2009) analyzed the 2003 National Survey of Children's Health and found higher rates of learning disabilities for children in poverty. Planty, M., Hussar, W., Snyder, T., Kena, G., KewalRamani, A., Kemp, J., et. al. (2009). *The condition of education 2009* (NCES 2009-081). Washington, DC: National Center for Education Statistics. Retrieved June 30, 2011 from http://nces.ed.gov/programs/coe/pdf/coe_gra.pdf
[134] National Center for Education Statistics. (2006). *The Condition of Education 2006* (NCES 2006-071). Washington, DC: Author. Retrieved June 30, 2011 from http://nces.ed.gov/programs/coe/pdf/coe_grr.pdf
[135] Office of Superintendent of Public Instruction. *Washington State Report Card*. Retrieved June 30, 2011 from http://reportcard.ospi.k12.wa.us/summary.aspx?year=2009-10
[136] Planty et al. (2009).
[137] We took the percentage of children in special education for up to 185% of the federal poverty level divided by the percentage of all children in the United States in special education to determine the factor by which to adjust Washington's special education rate. Altarac, M. & Saroha, E. (2007). Lifetime prevalence of learning disability among US children. *Pediatrics, 119*(Suppl. 1), S77-S83.
[138] McMahon, M. (2010). "The External Benefits of Education." In Brewer, D.J. & McEwan, P.J., eds. *Economics of education*. Oxford, UK: Academic Press.
[139] Acemoglu, D. & Angrist, J. (2000). How Large are Human-capital Externalities? Evidence from Compulsory Schooling Laws. *NBER Macroeconomics Annual* 15, 9-59.

(2011).[140] The high parameter is the contained in Bretton (2010).[141] In the model these values are used in a Monte Carlo draw from a triangular probability distribution with these three bounding parameters. The parameter is expressed as a multiple of the user-supplied private economic return to education; for example, if the user entered a private return to education of 0.10 and an external economic return parameter of 0.35, then the model monetizes the external economic benefits as 0.10 X 0.35 = 0.035 and this value is, in turn, multiplied times the valuation of private earnings.

Sources of Education Expenditures. The input screen allows users to input the proportion of education funding from state, local, and federal sources. We enter the same figures for all students and low-income students. Washington state sources are described in Exhibit 50 below.

Exhibit 50

Proportion of Marginal Education Costs by Source

	State	Local	Federal
Regular Education[1]	0.6700	0.2331	0.0969
Special Education[2]	0.8183	0.000	0.1817

[1] Washington State Office of the Superintendent of Public Instruction, *"Statewide Average Financial Tables and Charts"* for school year 2011-12, Table 3, available at: http://www.k12.wa.us/safs/PUB/FIN/1112/fs.asp.
[2] Washington State Office of the Superintendent of Public Instruction, *General Fund Expenditures by Program,* August 2012, available at: http://www.k12.wa.us/safs/PUB/FIN/1112/1112%20FinSum%20Section%202.pdf.

4.7b Valuation of Earnings from High School Graduation

For any program under consideration that measures high school graduation directly (or indirectly via a "linked" outcome), we use the CPS earnings data and other parameters to estimate the expected gain in life cycle labor market earnings.

First, the annual earnings and benefits are estimated for both high school graduates ($ModEarnHSG$) and non-high school graduates ($ModEarnNHSG$) with the following equations.

$$(4.60)\quad ModEarnHSG_y = \left(EarnHSG_y \times (1 + EscHSG)^{y-age}\right) \times \left(FHSG \times (1 + EscFHSG)^{y-age}\right) \times \left(IPD_{base}/IPD_{cps}\right)$$

$$(4.61)\quad ModEarnNHSG_y = \left(EarnNHSG_y \times (1 + EscNHSG)^{y-age}\right) \times \left(FNHSG \times (1 + EscFNHSG)^{y-age}\right) \times \left(IPD_{base}/IPD_{cps}\right)$$

For each year (y) from the age of a program participant (age) to age 65, the annual CPS earnings for the relevant group (either $EarnHSG$ or $EarnNHSG$, for high school graduates or non-high school graduates) are multiplied by one plus the relevant real earnings escalation rate (either $EscHSG$ or $EscNHSG$) raised to the number of years after program participation, times the relevant fringe benefit rate (either $FHSG$ or $FNHSG$) multiplied by one plus the relevant fringe benefit escalation rate (either $EscFHSG$ or $EscFNHSG$) raised to the number of years after program participation, times a factor to apply the Implicit Price Deflator for the base year dollars, IPD_{base}, chosen for the overall benefit-cost analysis relative to the year in which the CPS data are denominated, IPD_{cps}. In both equations, the two streams of earnings, $EarnHSG$ and $EarnNHSG$, are the annual estimates using the beta probability density distributions discussed above.

The gain in the present value of lifetime earnings from high school graduation is then estimated with this equation:

$$(4.62)\quad PVEarnGainHSG = \sum_{y=age}^{65} \frac{\left(ModEarnHSG_y - ModEarnNHSG_y\right) \times Units_{hsg} \times HSGCC}{(1 + Dis)^{y-age}}$$

For each year from the age of the program participant to age 65, the difference in earnings between high school graduates and non-high school graduates is multiplied by the increase in the number of high school graduation "units" (percentage points) caused by the program or policy. The calculation of the units variable is described in Chapter 2 and 3. This product is then multiplied by a parameter to measure the degree of causation ($HSGCC$) between the two present value earnings sums. This last term, which ranges from zero to one, can be used if there is evidence that the difference between the two earnings streams ($ModEarnHSG$ and $ModEarnNHSG$) is not due, causally, to obtaining a high school diploma but, instead, to other unobserved factors (such as motivation). A zero value for $HSGCC$ would imply no causal relationship between any observed differences in earnings, while a value of one would indicate that all of the difference in observed earnings is due to the possession of a high school diploma. Sources of estimates for the variable $HSGCC$ are described in

[140] Belfield, C., Hollands, F., & Levin, H. (2011). *What are the Social and Economic Returns?* New York: Columbia University, Teachers College, The Campaign for Educational Equity.
[141] Breton, T.R. (2010). Schooling and national income: How large are the externalities? Corrected estimates. *Education Economics 18*(4), 455-456.

Section 4.7a of this Chapter. The numerator in the equation is then discounted to the age of the program participant (*age*) with the discount rate (*Dis*) chosen for the overall benefit-cost analysis.

4.7c Valuation of Earnings from Increases in K–12 Standardized Student Test Scores

For any program under consideration that measures gains in student standardized test scores directly (or indirectly via a "linked" outcome), we use the CPS earnings data and other parameters to estimate the expected gain in life cycle labor market earnings.

First, the present value of lifetime earnings are estimated for all people, measured with the Current Population Survey with the following equation, where basic CPS earnings are adjusted for long-run real escalation rates and fringe benefit rates and converted into base year dollars, as described in Chapter 4.1. For each year, *y*, from the age of a program participant, *age*, to age 65, the modified annual CPS earnings, *ModEarnAll*, are multiplied by one plus the real earnings escalation rate, *EscAll*, raised to the number of years after program participation, times the fringe benefit rate, *FAll*, multiplied by one plus the fringe benefit escalation rate, *EscFAll*, raised to the number of years after program participation, times a factor to apply the Implicit Price Deflator for the base year dollars, IPD_{base}, chosen for the overall benefit-cost analysis relative to the year in which the CPS data are denominated, IPD_{cps}.

$$(4.63)\ \ ModEarnAll_y = \left(EarnAll_y \times (1 + EscAll)^{y-age}\right) \times \left(FAll \times (1 + EscFAll)^{y-age}\right) \times \left(IPD_{base}/IPD_{cps}\right)$$

The present value gain in earnings is then estimated. For each year from the age of the program participant to age 65, the modified earnings are multiplied by the increase in the number of test score "units" (standard deviation test score units) caused by the program or policy. The calculation of the units variable is described in Chapters 2 and 3. This term is then multiplied by a parameter to measure the degree of causation, *TSCC*, between a one standard deviation gain in student test scores and the related percentage increase in labor market earnings. Sources of estimates for the variable *TSCC* are described in Section 4.7a of this Chapter. The numerator in the equation is then discounted to the age of the program participant, *age*, with the discount rate, *Dis*, chosen for the overall benefit-cost analysis.

$$(4.64)\ \ PVEarnGainTS = \sum_{y=age}^{65} \frac{ModEarnAll_y \times Units_{ts} \times TSCC}{(1 + Dis)^{y-age}}$$

4.7d Valuation of Earnings from Increases in the Number of Years of Education Achieved

For any program under consideration that measures gains in the number of years of education achieved directly (or indirectly via a "linked" outcome), we use the CPS earnings data and other parameters to estimate the expected gain in life cycle labor market earnings.

First, the present value of lifetime earnings are estimated for all people measured with the Current Population Survey with the following equation, where basic CPS earnings are adjusted for long-run real escalation rates and fringe benefit rates and converted into base year dollars. For each year, *y*, from the age of a program participant, *age*, to age 65, the modified annual CPS earnings, *ModEarnAll*, are multiplied by one plus the real earnings escalation rate, *EscAll*, raised to the number of years after program participation, times the fringe benefit rate, *FAll*, multiplied by one plus the fringe benefit escalation rate *EscFAll* raised to the number of years after program participation, times a factor to apply the Implicit Price Deflator for the base year dollars, IPD_{base}, chosen for the overall benefit-cost analysis relative to the year in which the CPS data are denominated, IPD_{cps}.

$$(4.65)\ \ ModEarnAll_y = \left(EarnAll_y \times (1 + EscAll)^{y-age}\right) \times \left(FAll \times (1 + EscFAll)^{y-age}\right) \times \left(IPD_{base}/IPD_{cps}\right)$$

The present value gain in earnings is then estimated. For each year from the age of the program participant to age 65, the modified earnings are multiplied by the increase in the number of years of education "units" (in standard deviations) caused by the program or policy. The calculation of the units variable is described in Chapters 2 and 3. This term is then multiplied by a parameter to measure the degree of causation, *YearsOfEdCC*, between one extra year of education and the related percentage increase in labor market earnings. Sources of estimates for the variable *YearsOfEdCC* are described in Section 4.7a of this Chapter. The numerator in the equation is then discounted to the age of the program participant, *age*, with the discount rate, *Dis*, chosen for the overall benefit-cost analysis.

$$(4.66)\ \ PVEarnGainYearsofEd = \sum_{y=age}^{65} \frac{ModEarnAll_y \times Units_{yearsofed} \times YearsOfEdCC}{(1 + Dis)^{y-age}}$$

4.7e Valuation of Changes in the Use of K–12 Special Education and Grade Retention

The model can also calculate the value of two other K–12 educational outcomes: years of special education and grade retention. The present value cost of a year of special education is estimated by discounting the cost of a year in special education, *SpecEdCostYear*, for the estimated average number of years that special education is used, conditional on entering special education, *specedyears*. These years are assumed to be consecutive. The present value is to the age when special education is assumed to first be used, *start*. This sum is further present valued to the age of the youth in a program, *progage*, and the cost is expressed in the dollars used for the overall cost benefit analysis, *IPDbase*, relative to the year in which the special education costs per year are denominated, *IPDspecedcostyear*.

$$(4.67)\quad PVspeced_{start} = \sum_{y=1}^{specedyears} \frac{SpecEdCostYear}{(1+Dis)^{y}}$$

$$(4.68)\quad PVspeced_{progage} = \frac{PVspeced_{start} \times \dfrac{IPD_{base}}{IPD_{speced\,costyear}}}{(1+Dis)^{start-progage}}$$

The present value cost of an extra year of K–12 education is estimated for those retained for an extra year. This is modeled by assuming that the cost of the extra year of K–12 education, *EdCostYear*, after adjusting the dollars to be denominated in the base year dollars used in the overall analysis, would be borne when the youth is approximately 18 years old. Since there is a chance that the youth will not finish high school and, therefore, that the cost of this year will never be incurred, this present valued sum is multiplied by the probability of high school completion, *Hsgradprob*.

$$(4.69)\quad PVgraderet_{progage} = \left[\frac{EdCostYear \times \dfrac{IPD_{base}}{IPD_{ed\,costyear}}}{(1+Dis)^{18-progage}} \right] \times Hsgradprob$$

4.7f Adjustment Factors for Decaying Test Score Effect Sizes to Age 17

Many effective education programs increase the standardized test scores of program participants. The magnitude of these early gains, however, does not remain constant over time; researchers have found that test score gains from program participation "fade out" during the K–12 years.[142] Our meta-analyses include initial effects size for students' academic gains on standardized tests relative to the comparison group; an adjustment factor is then applied to this initial effect size to account for fade-out from the age of measurement to age 17. The relationships in the economic literature between test scores and labor market earnings are based on test scores late in secondary school; thus, it is critical to adjust earlier measurements of test scores appropriately.

We determined the adjustment factor by performing a multivariate regression analysis of 219 effect sizes spanning the post-test through grade 9 from 47 evaluations of early childhood education programs with multiple follow-up periods. We weighted the model by the inverse variance weight for random effects and included the type of test, type of program, and study research design rating as control variables. The results indicate that by grade 9, test score effect sizes were 41% lower than at post-test, on average. We projected these findings out to grade 12 for use in the benefit-cost model. Exhibit 51 displays the decay rates we used.

[142] For example, a meta-analysis by Leak et al. (2010) found that early test score gains decreased by at least 54% five or more years after the post-test; another meta-analysis by Camilli et al. (2010) estimated that early test score gains fade out by more than 50% by age 10; and Goodman & Sianesi (2005) examined fade-out for a single evaluation and found that early test score gains decreased by 30 to 50 percent per follow-up period. Leak, J., Duncan, G., Li, W., Magnuson, K., Schindler, H., & Yoshikawa H. (2010). *Is timing everything? How early childhood education program impacts vary by starting age, program duration, and time since the end of the program.* Paper prepared for presentation at the meeting of the Association for Policy Analysis and Management, Boston, MA; Camilli, G., Vargas, S., Ryan, S., & Barnett W. S. (2010). Meta-analysis of the effects of early education interventions on cognitive and social development. *Teachers College Record, 112*(3), 579-620; Goodman, A. & Sianesi, B. (2005). Early education and children's outcomes: How long do the impacts last? *Fiscal Studies, 26*(4), 513-548.

Exhibit 51

Age of measurement	Grade	Test score effect size as a percentage of post-test	Fadeout multiplier: Age 17 test score effect size as a percentage of the effect size at age of measurement
4	Pre-K	100%	47%
5	K	96%	49%
6	1	92%	51%
7	2	88%	53%
8	3	84%	56%
9	4	79%	59%
10	5	75%	62%
11	6	71%	65%
12	7	67%	69%
13	8	63%	74%
14	9	59%	79%
15	10	55%	85%
16	11	51%	92%
17	12	47%	100%

4.8 Valuation of Mental Health Outcomes

WSIPP's benefit-cost model contains procedures to estimate the monetary value of changes in certain mental health conditions. The model approximates mental health definitions established by the Diagnostic and Statistical Manual (DSM) of the American Psychiatric Association. The current model focuses on ADHD, Depression, Anxiety, and Disruptive Behavior. The latter category covers the DSM categories of Oppositional Defiant Disorder and Conduct Disorder. Obviously, there are other recognized mental health disorders. It is anticipated that future development of WSIPP's model will include additional categories. This section of the Benefit-Cost Technical Manual describes WSIPP's current procedures to estimate the monetary benefits of program-induced changes in these mental health conditions.

In general, WSIPP's mental health modeling follows the same analytic procedures described for in Chapter 4.4 for alcohol, tobacco, and illicit drugs. Readers can refer to that section to find more detail.

WSIPP's mental health model uses an incidence-based costing approach. It is not designed to provide an estimate of the total cost to society of current and past mental health disorders. Other studies have attempted to estimate these values.[143] For example, Insel (2008) summarizes findings indicating the total cost of serious mental illness in the United States in 2002 to be $317.6 billion in "economic" costs ($1,081 per capita) with x percent of this total due to health care expenditures, x percent due to loss in labor market earnings, and x percent due to disability payments.[144] These prevalence-based total cost studies can be interesting, but they are not designed to evaluate future marginal benefits and marginal costs of specific public policy options.

The purpose of WSIPP's model is to provide the Washington State legislature with advice on whether there are economically attractive evidence-based policies that, if implemented well, can achieve reductions mental health disorders. To do this, the model monetizes the projected life-cycle costs and benefits of programs or policies that have been shown to achieve improvements—today and in the future—in mental health conditions. If, for example, empirical evidence indicates that a mental health treatment program prevention program can reduce childhood ADHD symptoms, then what long-run benefits, if any, can be expected from this improved outcome? Once computed, the present value of these benefits can be stacked against program costs to determine the relative attractiveness of different approaches to achieve improvements in desired outcomes.

The current version of the mental health model allows the computation of the following types of avoided costs, or benefits, when a program or policy improves the mental health outcomes considered in this model. Depending on each particular mental health disorder, the following benefit or cost categories are included in WSIPP's model:

- Labor market earnings from mental health morbidity or mortality, to the degree there is evidence that current earnings are reduced because of mental health disorders (morbidity), or lifetime earnings are lost because of premature death (mortality) caused by mental health disorders.
- Health care costs for mental health morbidity, to the degree that these costs are caused by mental health conditions.
- Value of a statistical life (VSL) estimates, net of labor market gains, applied to the change in mortality (suicide) estimated to be caused by depression.

4.8a Input Screens for Mental Health Parameters.

WSIPP's mental health model is driven with a set of parameters describing various aspects of each disorder's epidemiology and linked relationships with other outcomes. These input parameters are shown on the following four screen shots. In addition, there are several other input parameters used in the mental health model that are general to WSIPP's overall benefit-cost model and these are discussed elsewhere in this Chapter. In the following sections, the sources for the parameters and the computational routines are described.

[143] See, for example, Harwood, H., Ameen, A., Denmead, G., Englert, E., Fountain, D., & Livermore, G. (2000). *The economic costs of mental illness, 1992*. Falls Church, VA: The Lewin Group. Retrieved June 30, 2011 from http://www.lewin.com/content/publications/2487.pdf; Greenberg, P. E., Kessler, R. C., Birnbaum, H. G., Leong, S. A., Lowe, S. W., Berglund, P. A., & Corey-Lisle, P. K. (2003). The economic burden of depression in the United States: How did it change between 1990 and 2000? *Journal of Clinical Psychiatry, 64*(12), 1465-1475.; Kessler, R. C., Heeringa, S., Lakoma, M. D., Petukhova, M., Rupp, A. E., Schoenbaum, M.. . . Zaslavsky, A. M. (2008). Individual and societal effects of mental disorders on earnings in the United States: Results from the National Comorbidity Survey Replication. *American Journal of Psychiatry, 165*(6), 703-711.

[144] Insel, T. R. (2008). Assessing the economic costs of serious mental illness. *American Journal of Psychiatry, 165*(6), 663-665.

Exhibits 52 through 55 display the parameters for the analysis of mental health disorders.

Exhibit 52
ADHD

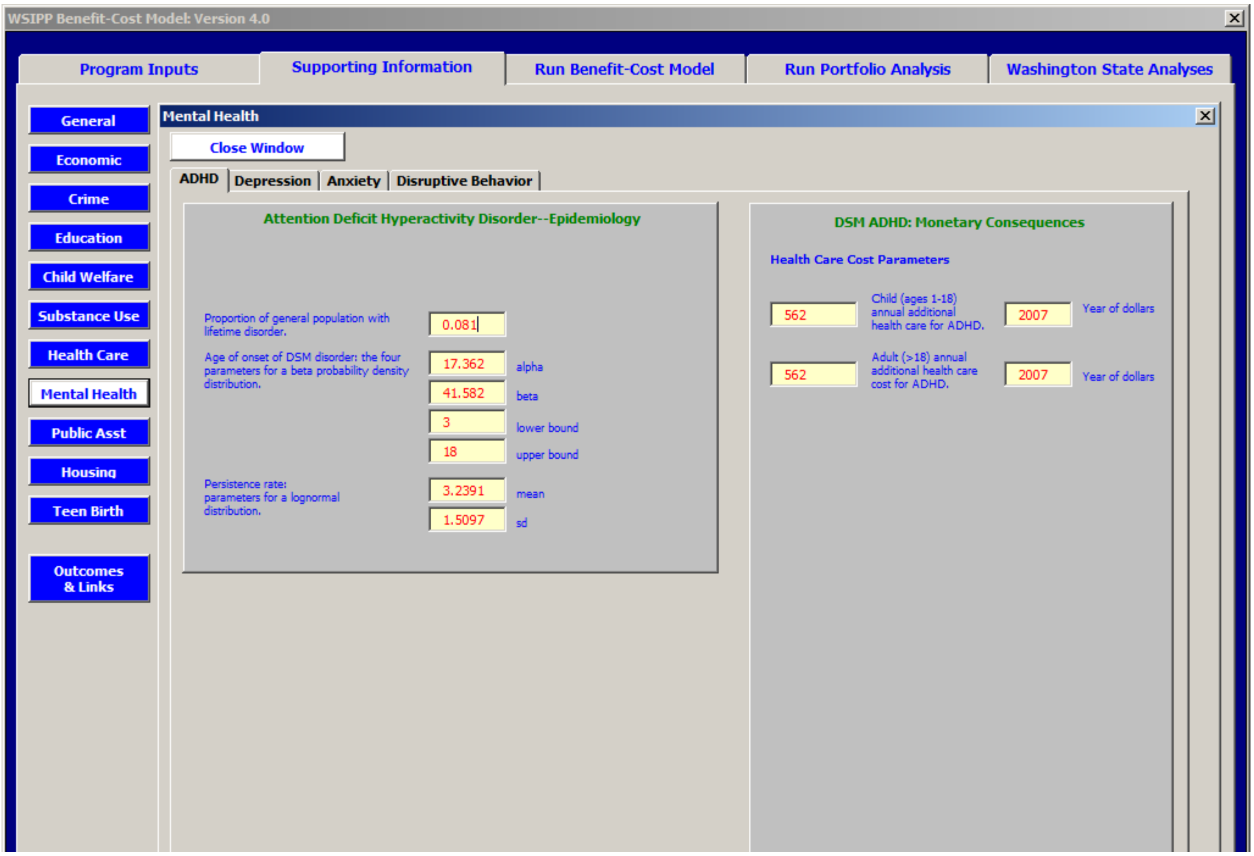


Exhibit 53
Depression

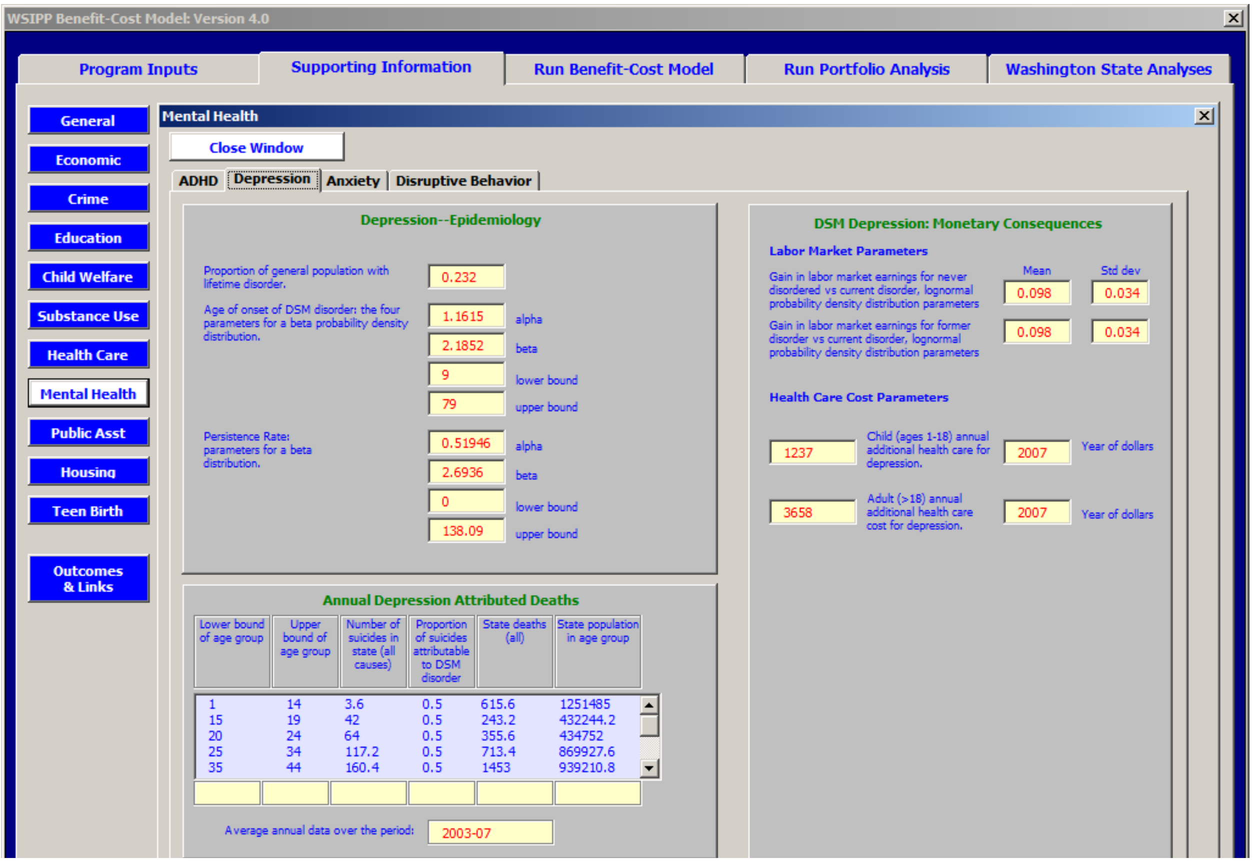


Exhibit 54
Anxiety

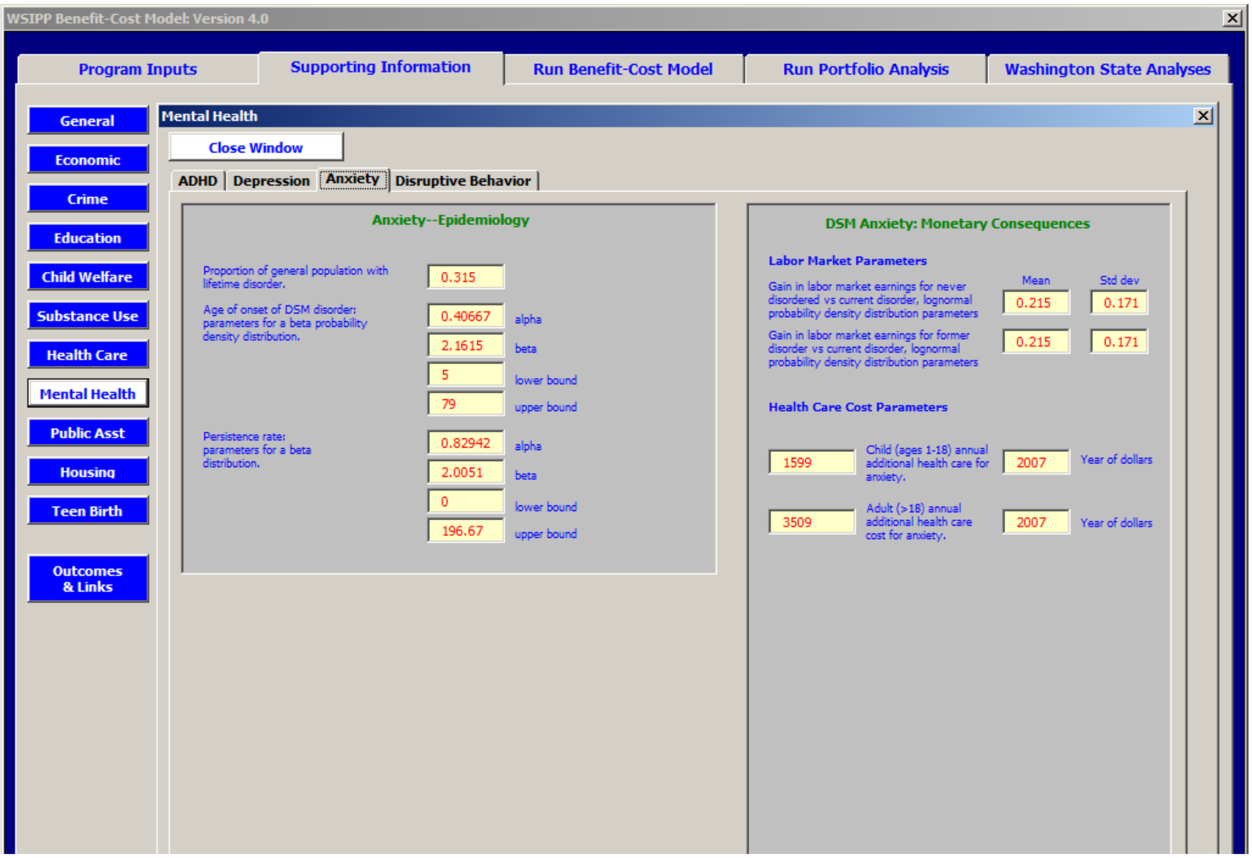
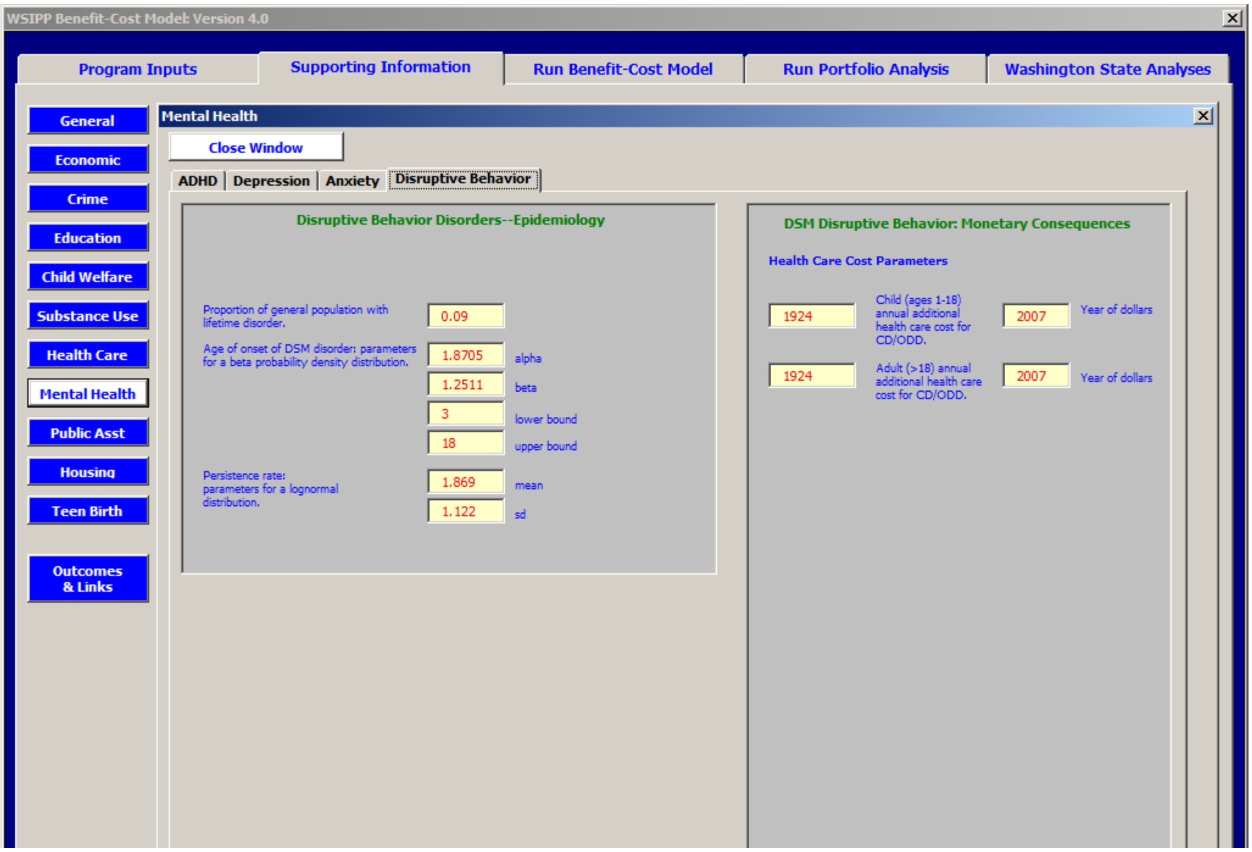


Exhibit 55
Disruptive Behaviors



4.8b Mental Health Epidemiological Parameters

WSIPP's mental health model begins by analyzing the epidemiology of each mental health disorder to produce estimates of the current 12-month prevalence. An estimate of the current prevalence of each disorder is central to the benefit-cost model because, for dichotomously measured outcomes, it becomes the "base rate" to which program or policy effect sizes are applied to calculate the change in the number of avoided mental health "units" caused by the program, over the lifetime following treatment.

Four parameters enter the model to enable an estimate of the current prevalence of each mental health disorder, from age 1 to age 100.

- **Lifetime prevalence**: the percentage of the population that has a specific lifetime mental health disorder.
- **Age of onset**: the age of onset of the specific mental health disorder.
- **Persistence**: the persistence of the specific mental health, given onset.
- **Death (Survival)**: the probability of death by age, after the age of treatment by a program.

The parameters that enter the model appear on each screen shot on Exhibits 52 through 55. Exhibit 56 also displays the current parameters in WSIPP's model for the first three epidemiological factors, along with sources and notes. The death probability information is described elsewhere in this Chapter.

For each mental health disorder, the current prevalence of the disorder is estimated with this equation.

$$(4.70) \quad CP_y = \left(\sum_{0=1}^{y} 0_0 \times P_{(y-0+1)} \right) \times LTP \times S_y$$

The current disorder prevalence probability at any year in a person's life, CP_y, is computed with information on the age-of-onset probability, O, from prior ages to the current age of the person, times the persistence probability, P, of remaining in the DSM condition at each onset age until the person is the current age, times the lifetime probability of ever having the DSM disorder, LTP, times the probability of survival at each age, S_y, following treatment by a program.

For each mental health disorder, the exogenous age-of-onset probability distribution for ages 1 to 100, O, is a density distribution and is estimated with information from the sources shown in Exhibit 56. The parameters in Exhibit 56 are the same as those entered by the user on the screen shots in Exhibits 52 through 55.

$$(4.71) \quad 1 = \sum_{y=1}^{100} O_y$$

Also, for each mental health disorder, the exogenous persistence distribution for ages after onset, P, is computed from the sources shown in Exhibit 56. The persistence distribution describes the probability, on average, of being in the DSM disorder condition each year following onset.

The probability of survival at any given age, S_y, is computed from a national life table on survival, LTS, in the general population. The inputs for the survival table are described in another section of this Benefit-Cost Technical Manual. To compute the current prevalence of a disorder over the entire life course, S_y is normalized to age one.

$$(4.72) \quad S_y = \frac{LTS_y}{LTS_1}$$

Since the probability of survival depends on the number still living at the treatment age, $Tage$, the S_y is normalized to the age of the person being treated in the program being analyzed, since it is assumed that all treatment programs will be for those currently alive at time of treatment.

$$(4.73) \quad S_y = \frac{LTS_y}{LTS_{Tage}}$$

Equation 4.70 describes the calculation of current prevalence for general (prevention) populations. For programs treating indicated populations, CP_y in equation 4.74 describes the prevalence in all years following treatment.

$$(4.74) \quad CP_y = \frac{\sum_{0=1}^{tage} 0_0 \times P_{(y-0+1)}}{\sum_{0=1}^{tage} 0_0} \times S_y \times SF$$

The additional term in equation 4.74 is the reduced chance of survival for someone with depression. We compute an estimate for this as a single parameter with the following equation.

$$(4.75) \quad SF = \frac{\sum_{a=1}^{A}\left(Pop_a \times CP_a \times \frac{\frac{(PopD_a - DeprD_a)}{Pop_a}}{\frac{PopD_a}{Pop_a}}\right)}{\sum_{a=1}^{A}(Pop_a \times CP_a)}$$

In this equation, $Popa$ is the total population in a state in each age group, CP_a is the average current depression disorder prevalence in each age group, $PopD_a$ is the total number of deaths in a state in each age group, and $Depr_a$ is the deaths attributable to depression-induced suicides in each age group. The suicide data are entered on Exhibit 53. The suicide death data are obtained from the Washington State Department of Health.

Exhibit 56
Input Parameters for the Epidemiology of Mental Health Disorders

	DSM ADHD	DSM Depression	DSM Anxiety	Disruptive Behavior
	(a)	(b)	(c)	(d)
Percent of population with lifetime DSM disorder[1]	8.1%	23.2%	31.5%	9.0%
Age of onset				
Type of distribution[2]	Beta-general	Beta-general	Beta-general	Beta-general
Parameter 1	17.362	1.1615	.40667	1.8705
Parameter 2	41.582	2.1852	2.1615	1.2511
Parameter 3	3	9	5	3
Parameter 4	18	79	79	18
Persistence of DSM disorder, given onset				
Type of distribution[3]	Lognormal	Beta-general	Beta-general	Lognormal
Parameter 1	3.2391	.51946	.82942	1.869
Parameter 2	1.5097	2.6936	2.0051	1.122
Parameter 3	n/a	0	0	n/a
Parameter 4	n/a	138.09	196.67	n/a

Notes and sources

1. Kessler, R.C., Berglund, P., Delmer, O., Jin, R., Merikangas, K.R., & Walters, E.E. (2005). Lifetime prevalence and age-of-onset distributions of DSM-IV disorders in the National Comorbidity Survey Replication. Archives of General Psychiatry, 62(6): 593-602. Estimates from Table 3; the estimate for disruptibe behavior is an average of the reported risk for oppositional-defiant disorder and conduct disorder.
2. All age of onset distributions were fit with data reported in Kessler, R.C., Berglund, P., Delmer, O., Jin, R., Merikangas, K.R., & Walters, E.E. (2005). Lifetime prevalence and age-of-onset distributions of DSM-IV disorders in the National Comorbidity Survey Replication. Archives of General Psychiatry, 62(6): 593-602. From Table 3 in the paper, we estimated probability density distributions for the age of onset of each of the four mental health disorders, conditional on having a disorder. @Risk software was used to estimate alternative distributions; the distribution with the best fit (criterion: lowest root-mean squared error) was chosen. Beta-general distributions were the best fitting.
3. To estimate persistence of DSM mental health disorders we used the publicly available information from the National Comorbidity Survey-Replication (NCS-R). The NCS-R surveyed a representative sample of 9,282 adults in the United States in 2001-03 to estimate prevalence of mental illnesses in the U.S. population. We identified persons with a lifetime diagnosis of attention deficit, behavioral, any anxiety major depressive disorders. For each disorder we calculated the interval from first to last episode. Those without an episode in the prior 12 months were considered to be free of the disorder. For each disorder, we used survival analysis and the appropriate survey weight to model time to remission. We then used these data to fit the parameters of probability distributions that fit the data. @Risk software was used to estimate alternative distributions; the distribution with the best fit (criterion: lowest root-mean squared error) was chosen, and the winning distribution, and its parameters, is shown for each mental health disorder.

4.8c Linkages: Mental Health to Other Outcomes

WSIPP's benefit-cost model monetizes improvements in mental health outcomes, in part, with linkages between each mental health outcome and other outcomes to which a monetary value can be estimated. The parameters for these linkages are obtained by a meta-analytic review of relevant research literature. For example, we estimate the relationship between DSM mental health conditions and labor market earnings by meta-analyzing the most credible studies that have addressed this topic. The meta-analytic process provides both an expected value effect given the weight of the evidence, and an estimate of the error of the estimated effect. Both of these two parameters are entered into the benefit-cost model and used when performing a Monte Carlo simulation. The linkages in the current WSIPP model are listed in Chapter 5.

4.8d Human Capital Outcomes Affecting Labor Market Earnings via Mental Health Morbidity and Mortality

The WSIPP model computes lost labor market earnings as a result of mental health morbidity and mortality when there is evidence that the linkage is causal. The procedures begin by estimating the labor market earnings of an average person with a current DSM mental health disorder. As described in Chapter 4.1, WSIPP's model uses national earnings data from the U.S. Census Bureau's Current Population Survey. The CPS data used in this analysis represent average earnings of all people, both workers and non-workers at each age.

Using the same methods as for ATOD, for each person at each age, total CPS earnings can be viewed as a weighted sum of people who have never had a mental health disorder, plus those that are currently disordered, plus those that were formerly disordered but do not currently have a disorder. From the CPS data on total earnings for all people, the earnings of individuals with a current mental health condition, at each age, y, is computed with this equation:

$$(4.76)\quad EarnC_y = \frac{EarnAll_y \times (1+EarnEscAll)^{y-tage} \times EarnBenAll \times (1+EarnBenEscAll)^{y-tage} \times \left(IPD_{base}/IPD_{cps}\right)}{\left((1+EarnGN) \times \left(1-\left(CP_y + \left(\sum_{o=1}^{y}(O_o \times LTP) - CP_y\right)\right)\right) + (1+EarnGF) \times \left(\sum_{o=1}^{y}(O_o \times LTP) - CP_y\right) + CP_y\right)}$$

The numerator in equation 4.76 includes the CPS earnings data for all people, $EarnAll$, with adjustments for real earnings growth, $EarnEscAll$, earnings-related benefits, $EarnBenAll$, growth rates in earnings benefits, $EarnBenEscAll$, and an adjustment to denominate the year of the CPS earnings data, $IPDcps$, with the year chosen for the overall analysis, $IPDbase$. These variables are described in Chapter 4.1.

The denominator in equation 4.76 uses the epidemiological variables described above: age of onset probabilities, Oy, lifetime prevalence rates, LTP, and current 12-month prevalence rates, CPy, at each age.

The denominator also includes two variables on the earnings gain of never-disordered people compared to currently disordered people, $EarnGN$, and the earnings gain of formerly disordered people compared to currently disordered people, $EarnGF$. These two central relationships measure the effect of a DSM mental health condition on labor market success (as measured by earnings). These relationships are derived from meta-analytic reviews of the relevant research literature as listed in Chapter 5.

For mental health disorders, we meta-analyzed two sets of research studies: one set examines the relationship between mental health disorders and employment rates, and the second examines the relationship between mental health disorders and earnings, conditional on being employed. Exhibit 68 in Chapter 5 displays the results of our meta-analysis of these two bodies of research for DSM mental health disorders. Our meta-analytic procedures are described elsewhere in this Chapter.

For a mental health disorder, from these two findings—the effect of a mental health disorder on employment, and the effect of a mental health disorder on the earnings of those employed—we then combine the results to estimate the relationship between a mental health disorder and average earnings of all people (workers and non-workers combined). To do this, we use the effect sizes and standard errors from the meta-analyses on employment and earnings of workers. We use data from the 2009 CPS earnings for average earnings of those with earnings and the standard deviation in those earnings and the proportion of the CPS sample with earnings. We then compute the mean change in earnings for all people by computing the change in the probability of earnings and the drop in earnings for those with earnings. The ratio of total earnings (for both workers and non-workers) for non-disordered individuals to mental health disordered individuals is then computed.

This mean effect, however, is estimated with error as measured by the standard errors in the meta-analytic results reported above. Therefore, we use @RISK distribution fitting software to model the joint effects of an alcohol disorder on the mean ratio, given the errors in the two key effect size parameters. The distribution with the best fit (criterion: lowest root-mean squared error) is a lognormal distribution. Therefore, the two lognormal distribution parameters are entered in the model, as shown in Exhibits 41 and 42. Since the body of evidence we reviewed in the meta-analysis did not allow separation of the effects into (1) never disordered people vs. currently disordered people, and (2) formerly disordered people vs. currently disordered people, we enter the same lognormal parameters for both the $EarnGN$ and the $EarnGF$ variables.

The present value of the change in morbidity-related earnings for a prevention program that produces a change in the probability of a current mental health disorder is given by:

$$(4.77)\quad PV\Delta Earn = \sum_{y=tage}^{65} \frac{\left(\Delta MH_y \times \left(1-\sum_{o=1}^{y} O_o\right) \times EarnGN \times EarnC_y\right) + \left(\Delta MH_y \times \left(1-\left(1-\sum_{o=1}^{y} O_o\right)\right) \times EarnGF \times EarnC_y\right)}{(1+dis)^{(y-tage+1)}}$$

Where *ΔMHy* is the change in mental health disorder probability; *O* are the annual onset probabilities; *EarnGN* is the earnings gain of never-disordered people compared to currently disordered people; *EarnGF* is the earnings gain of formerly disordered people compared to currently disordered people; *dis* is the discount rate; and *tage* is the treatment age of the person in the program. Since a prevention program may serve people without a disorder and with a disorder, the above model weights that probability by the age of onset probabilities.

The present value of the change in the morbidity-related earnings for a treatment program that produces a change in the probability of people with a current mental health disorder is given by:

$$(4.78)\quad PV\Delta Earn = \sum_{y=tage}^{65} \frac{\left(\Delta MH_y \times EarnGF \times EarnC_y\right)}{(1+dis)^{(y-tage+1)}}$$

This model for a treatment program is simpler than that for a prevention program because, by definition, a treatment program only attempts to turn currently disordered people into formerly disordered people.

$$(4.79)\quad PVL{:}P_{mort} = \sum_{a=A}^{100} \frac{PE_a \times R_a \times \sum_{y=a}^{100}\left(LC_y \times (1+LGN)\right) \times DeathPrP_a + PE_a \times (1-R_a) \times \sum_{y=a}^{100}\left(LC_y \times (1+LGF)\right) \times DeathPrP_a}{(1+Dis)^a}$$

For labor market morbidity-related benefits for treatment programs, the labor market benefits of mental health disorder reductions are computed with this equation:

$$(4.80)\quad PVL{:}T_{morb} = \sum_{a=A}^{100} \frac{LC_a \times LGF \times PE_a}{(1+Dis)^a}$$

4.8e Medical Costs

WSIPP's model computes health care costs incurred (or avoided) with changes in the mental health conditions modeled. The inputs for these parameters are shown on Exhibits 52 through 55. They were computed from an analysis of data from the federal Medical Expenditure Panel Survey (MEPS).

Estimates for Mental Disorders:

The MEPS is a nationally representative large-scale survey of American families, medical providers, and employers who report on healthcare service utilization and associated medical conditions, costs, and payments. An annual cost of healthcare services for 2007 was calculated by adding the costs of inpatient, outpatient, emergency room, home health, and prescription medication costs per individual. This figure was regressed on a dummy variable representing a mental disorder of interest, controlling for demographic variables, psychiatric comorbidity, and other factors that might be expected to simultaneously correlate with mental illness and inflate total healthcare costs (e.g., existence of chronic illnesses, child delivery, health insurance). The resulting regression coefficient for each disorder represents an estimate of the additional cost of healthcare service utilization per year to individuals with the disorder versus without it. Separate regression models were conducted for adults (over 18 years old) and children, because the coefficients for some disorders were different by age groups.

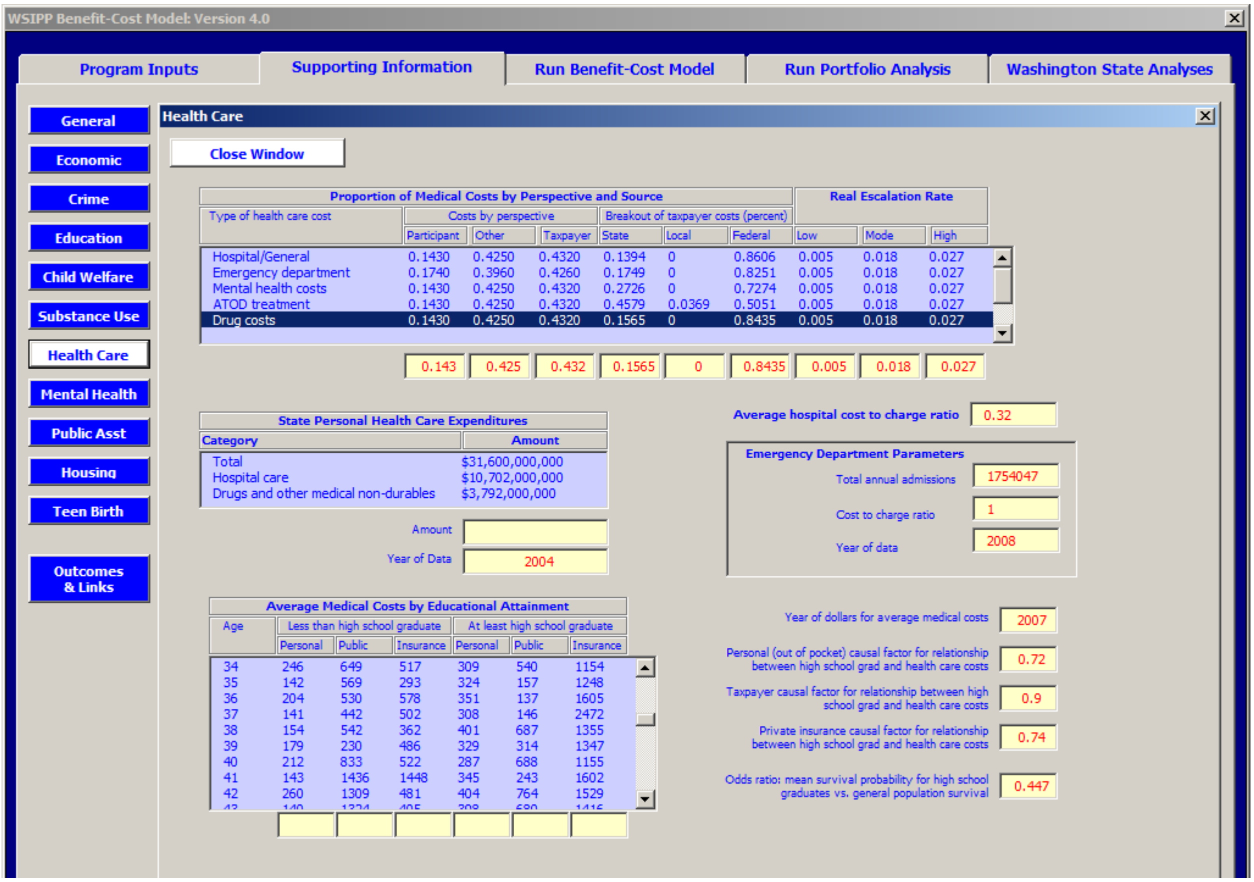
The costs described above were modified in several ways: first, to compute costs reflective of the present time, figures from the 2007 MEPS were adjusted for inflation and escalation in healthcare costs over time. Second, we were concerned that for some disorders the psychosocial interventions we reviewed would not substitute for medication use (i.e., that medications would continue to be a cost for individuals with this disorder even after successful psychosocial treatment). If this were the case, our figures— based on a total annual cost that includes prescription medications— would overestimate the benefits that would be expected from an effective intervention. Thus, for several disorders (ADHD, Bipolar Disorder, Schizophrenia), medication costs were removed from the total annual costs, such that the additional costs attributed to these disorders are only for inpatient, outpatient, emergency room, and home health services. Lastly, some disorders (e.g., Conduct and Oppositional Defiant Disorders) are reported by so few MEPS respondents that we were concerned about the representativeness of these individuals relative to the larger population. In such cases, we applied figures from analyses of other disorders that we believed to be similar (for instance, figures for CD/ODD are derived from analyses of ADHD).

4.9. Valuation of Health Care Outcomes

The benefit-cost model uses a number of health care parameters. These are shown on the screen shot in Exhibit 57.

Total Washington personal health care expenditures are collected for 2004, the most recent year available from the Centers for Medicare & Medicaid Services, U.S. Department of Health & Human Services.[145] Information on who pays for personal health care expenditures is from the same source, but uses more recent 2009 national data.[146]

Exhibit 57



A hospital cost-to-charge ratio for Washington State is computed with 2009 data from the Healthcare Cost and Utilization Project (HCUP) of the U.S. Department of Health & Human Services.[147]

An estimate of the long-run real escalation rate in per capital inflation-adjusted personal health care costs is computed from the 2009-2019 forecast from Centers for Medicare & Medicaid Services, U.S. Department of Health & Human Services.[148] The Washington state model currently uses the same inputs for all types of health care costs, but the model allows separate estimates for each type of cost.

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[145] Centers for Medicare & Medicaid Services, *Health expenditures by state of residence, 1991-2004*. Retrieved June 30, 2011 from http://www.cms.gov/NationalHealthExpendData/05_NationalHealthAccountsStateHealthAccountsResidence.asp#TopOfPage

[146] Centers for Medicare & Medicaid Services, U.S. Department of Health & Human Services. Retrieved June 30, 2011 from http://www.cms.gov/NationalHealthExpendData/downloads/tables.pdf, Table 6, data for 2009.

[147] Agency for Healthcare Research and Quality, Healthcare Cost and Utilization Project: http://hcupnet.ahrq.gov/

[148] Centers for Medicare & Medicaid Services. (n.d.). *National health expenditure projections 2009-2019*. United States Department of Health & Human Services, Author. Retrieved June 30, 2011 from http://www.cms.gov/NationalHealthExpendData/downloads/proj2009.pdf

Total annual emergency room visits in Washington for 2008 is computed from data compiled by the Washington State Hospital Association.[149] Information on emergency room charges by type of payer are obtained from the Agency for Healthcare Research and Quality, U.S. Department of Health & Human Services.[150]

The model allows the user to input the proportional sources of state, local, and federal funding for the different types of health care expenditures. Washington state values are described in Exhibit 58 below.

Exhibit 58

Proportion of Health Care Costs by Source

	State	Local	Federal
Hospital/General Health Care[1]	0.1394	0.0000	0.8606
Emergency Department[1]	0.1749	0.0000	0.8251
Mental Health costs[1]	0.2726	0.0000	0.7274
ATOD Treatment[2]	0.4579	0.0369	0.5051
Drug/Pharmacy costs[1]	0.1565	0.0000	0.8435

[1] Estimates calculated from 2010 Medical Expenditure Panel Survey data, available at: http://meps.ahrq.gov/mepsweb/data_stats/quick_tables_results.jsp?component=1&subcomponent=0&year.
[2] Percentages from Washington State Department of Social and Health Services report: *"Overview of Publicly Funded Services Substance Use Prevention, Treatment and Recovery,"* available at: http://www.dshs.wa.gov/pdf/dbhr/WASubstanceUseServicesOverview03-20-13.pdf.

Health Care Cost Estimates for High School Graduation Compared to less than High School Graduation

As noted in the previous section of the Chapter, the Medical Expenditure Panel Survey (MEPS) is a nationally representative large-scale survey of American families, medical providers, and employers who report on healthcare service utilization and associated medical conditions, costs, and payments. An annual cost of services paid by public (e.g., Medicaid, Medicare), private (i.e., insurance), and personal (i.e., family out-of-pocket) sources was computed for 2007 (the latest available year of the MEPS). Among adults, mean costs were analyzed by age and high school graduation status (whether the individual has at least a high school diploma), such that at each age a difference between those with and without a diploma in public, private, and personal costs could be computed.

These mean differences are descriptive in nature and do not account for demographic or other differences between individuals with and without a high school diploma that could influence healthcare costs. As such, ordinary least squares (OLS) regression models were conducted for each payment source. First, we analyze a sparsely controlled model, which produces a regression coefficient for the additional cost of having a diploma that was similar to the descriptive data. Next, we analyze a regression model that includes multiple covariates for demographic variables as well as other factors that might be expected to simultaneously correlate with education and inflate total healthcare costs (e.g., childbirth). As expected, the regression coefficient for having a high school diploma in the highly controlled model is smaller than the sparsely controlled model. The difference between the estimates from these two models is reflected in the “causal factor” listed for each payment source (public, private, personal) in the screen shot. For example, the difference in personal healthcare costs between individuals with and without a high school diploma is not the mean difference displayed in the blue table, but that difference multiplied by 0.72.

[149] Washington State Hospital Association. (2010). *Emergency room use*. Seattle, WA: Author. The table on page 4 reports 18 months of emergency department visits for January 2008 to June 2009. This sum was multiplied by 2/3 to convert to an annual figure representing the year 2008.
[150] Agency for Healthcare Research and Quality, Healthcare Cost and Utilization Project: http://hcupnet.ahrq.gov/

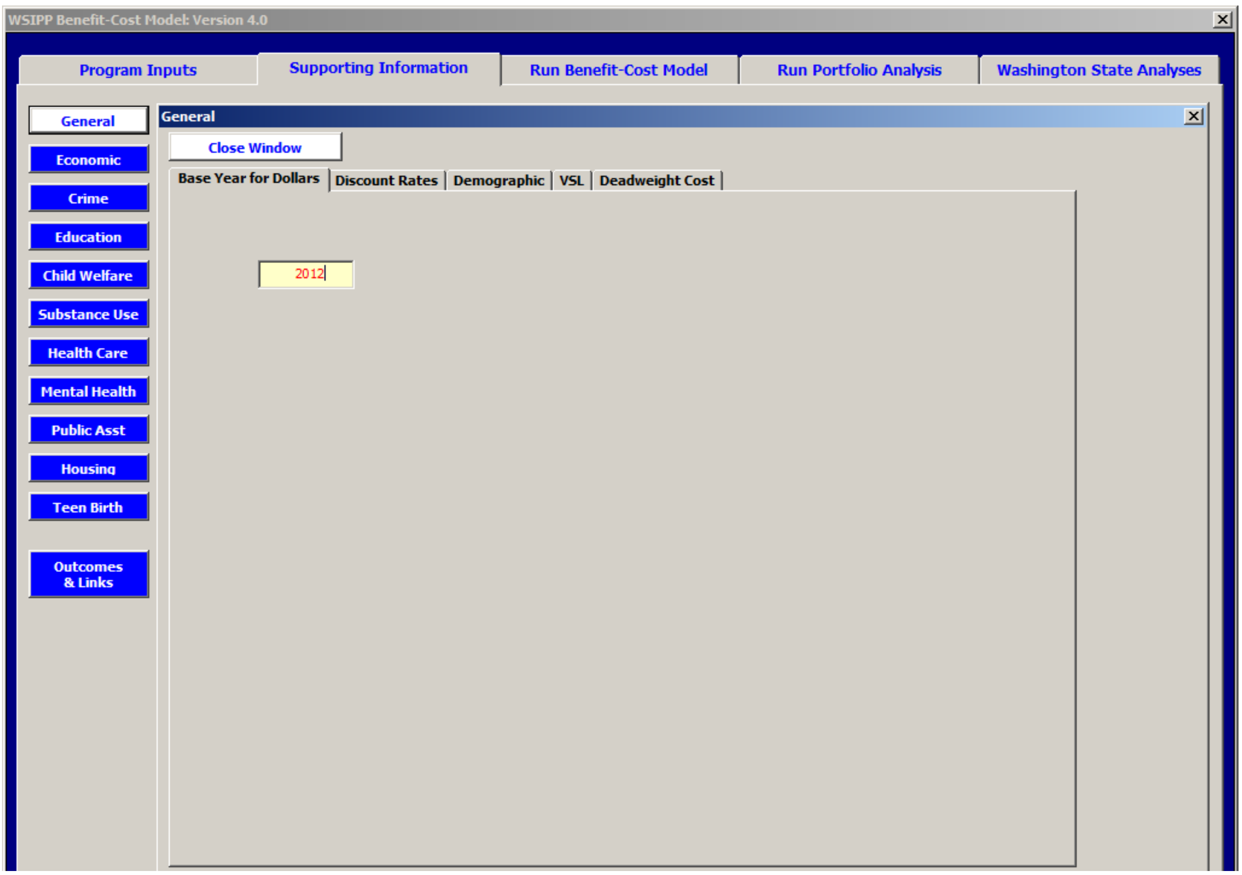
4.10 Other Parameters

In addition to the parameters discussed in the previous sections of this Chapter, the model uses a number of additional user-supplied inputs to compute benefits and costs. These are discussed in this section.

4.10a Base Year for Monetary Denomination

The model contains many price and monetary values; each is denominated in a particular year's monetary values. To express all monetary values in a common year, the user selects a base year. When the model runs, all monetary values entered into the model are converted to the base year values with the price index chosen by the user (see Section 4.10d). The input screen for the base year is shown in Exhibit 59.

Exhibit 59



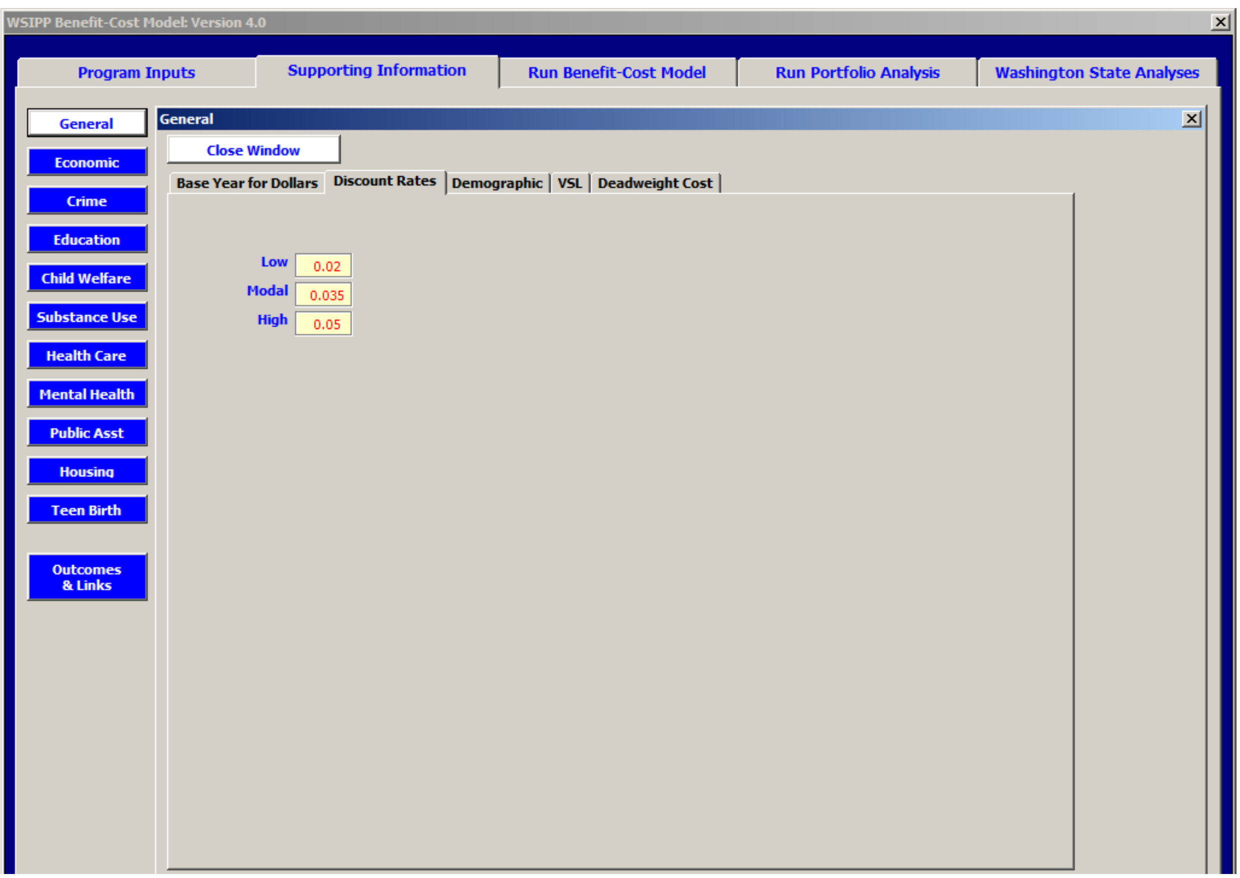
4.10b Discount Rates

The model uses a range of real discount rates to compute net present values. The discount rates are applied to all annual benefit and cost cash flows and presented-valued to the time the investment would be made. Equation 4.81 indicates that the net present value of a program, evaluated at the at the age of a person for whom an investment is made, NPV_{age}, is the discounted sum of benefits at each year, B_y, minus program costs at each year, C_y, discounted with a discount rate, Dis.

$$(4.81)\quad NPV_{age} = \sum_{y=age}^{N} \frac{B_y - C_y}{(1 + Dis)^y}$$

The model uses low, modal, and high discount rates in computations. When the model is run in non-simulation mode, the modal discount rate is used. In Monte Carlo simulation, each run randomly draws a discount rate from a triangular probability density distribution, with the user-selected low, modal, and high discount rates defining the triangle. Exhibit 60 is a screen shot showing where the three discount rates are entered. WSIPP uses a low real discount rate of 2%, a modal rate of 3.5%, and a high rate of 5%. These input choices reflect the recommended rates in Moore et al. (2004).[151] Similarly, the Congressional Budget Office has used a 3% real discount rate in its analyses of Social Security.[152] Heckman et al. (2010) analyzed the benefits and costs of the Perry Preschool program and employed a range of discount rates; they used a 3% rate to summarize the main benefit-cost results.[153]

Exhibit 60

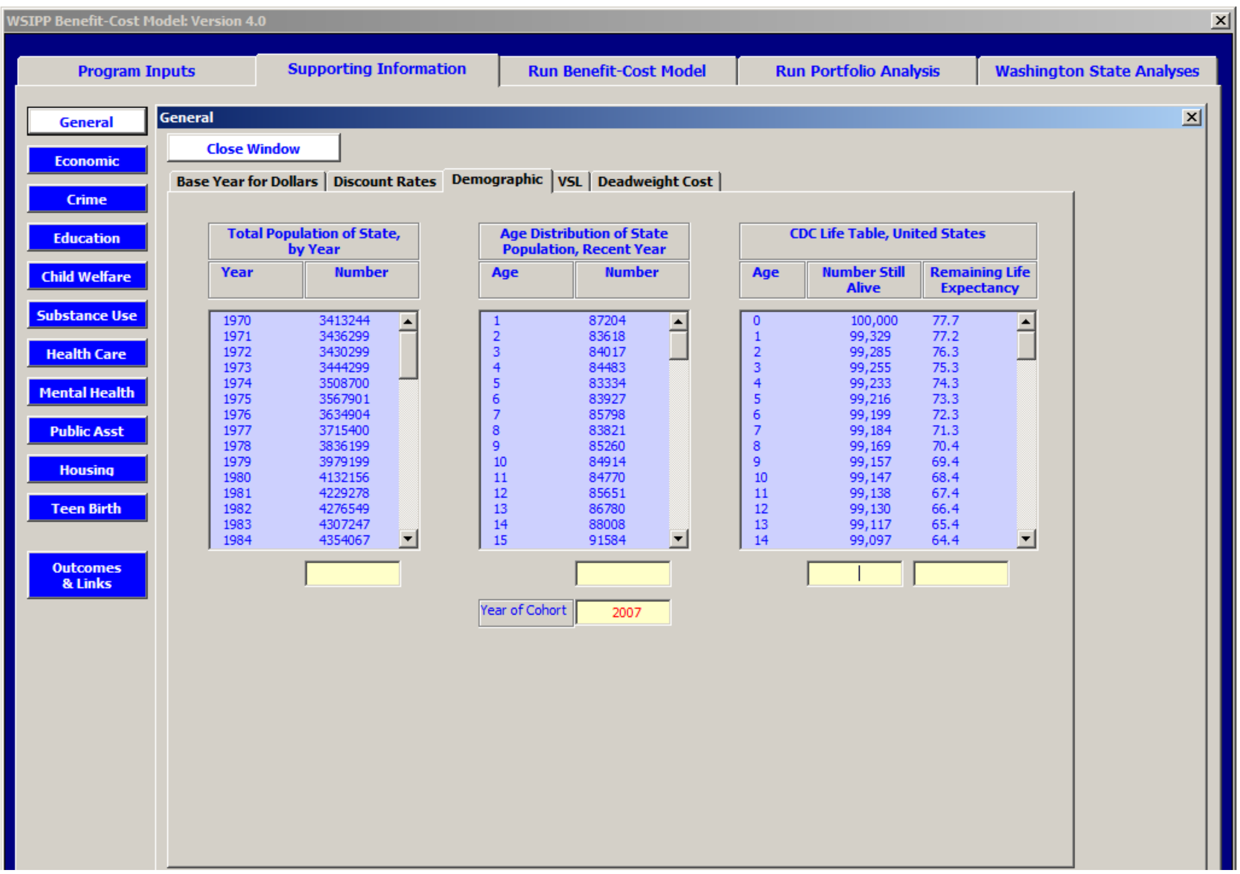


[151] Moore, M. A., Boardman, A. E., Vining, A. R., Weimer, D. L., & Greenberg, D. H. (2004). Just give me a number! Practical values for the social discount rate. *Journal of Policy Analysis and Management, 23*(4), 789-812.
[152] Congressional Budget Office. (2012). *The 2012 Long-Term Projections for Social Security: Additional Information*. Washington, DC: Author. Retrieved August 8, 2013 from http://www.cbo.gov/sites/default/files/cbofiles/attachments/43648-SocialSecurity.pdf
[153] Heckman et al. (2010).

4.10c Demographic Information

Several of the computations in the model require basic demographic information about population in the jurisdiction to which the model is applied. Exhibit 61 displays the screen shot for these inputs. The total annual population for the jurisdiction by year is included along with a forecast. For Washington State, we enter the total state population estimates from the Washington State Office of Financial Management (OFM), the official forecasting agency for the state. The model also requires information on the current distribution of the state population by single year of age. For Washington, we enter this information as supplied by OFM. Finally, the model needs a recent life table with information on the number of people in a birth cohort surviving to each year along with the life expectancy. We use life table information for the United States produced by the U.S. Department of Health and Human Services Centers for Disease Control and Prevention.[154]

Exhibit 61



[154] Arias, E. (2010). *United States life tables, 2006* (National Vital Statistics Reports vol. 58, no. 21). Washington, DC: United States Department of Health and Human Services, National Vital Statistics System, Table 1.

4.10d Valuation of Reductions in Mortality Risk: Value of a Statistical Life

Several of the outcomes analyzed in WSIPP's benefit-cost model affect the risk of mortality. For example, as described in Chapter 4.4, if a prevention program reduces the risk that a participant will have a DSM alcohol disorder, then there is evidence that there will also be a reduced risk of an earlier-than-expected death.

The benefit-cost model employs two procedures to monetize the change in mortality risk.[155]

The first procedure is sometimes called the "human capital" approach. This approach estimates the present value of lifetime labor market earnings that are lost because of an early death. In addition to lost labor market earnings, analysts sometimes include values of lost household production, valued at labor market rates, in the event of a death. As described in other sections of this Chapter, WSIPP's model computes estimates for these lost human capital values using standard present-value procedures.

While the human capital approach places a monetary value of lost labor production, it does not provide an overall estimate of how much people would be willing to pay (or accept) for changes in mortality risk. To address this broader perspective, economists have been developing empirical estimates of the monetary value that people place on their lives. The general approach entails computing the value of a statistical life (VSL).[156] The VSL estimates are almost always much larger than the lost earnings from the human capital approach because VSL measures the total monetary value that people place on reduced risks of death, or the amounts that they are willing to accept for increased levels of mortality risk, and lost labor market earnings are only a portion of those valuations.

There are two general approaches used to calculate VSL: (1) the "revealed preferences" estimated from compensating wage differentials, and (2) the "stated preferences" elicited from people in surveys on how much they would be willing to pay to reduce the risk of death. Both approaches are active areas of current research and, among the more recent studies, the two approaches have been producing estimates that include quite similar ranges. Cropper, et al. (2011) reviewed both approaches and found that the revealed preference studies produce estimates of $2.0 million to $11.1 million (2009 USD), and that the stated preference studies produce VSL's in the range of $2.0 million to $8.0 million (2009 USD).

In addition to the current research on the calculation of an overall VSL, researchers are focusing on the heterogeneity of VSL by age and by risk level. Aldy and Viscusi (2008), after constructing revealed preference wage equations, have provided recent estimates of VSL for ages 18 to 62.[157] And Hammitt and Haninger (2010) have used a stated preference approach to estimate the VSL that adults place on children, compared to the VSL they state for adults.[158]

WSIPP's current approach to VSL includes specifying a range of VSLs to be used with Monte Carlo simulation, and applying the results from Aldy and Viscusi (2008) and Hammitt and Haninger (2010) to distribute VSL to individual years of a person's life. After computing these values, we then compute an adjusted VSL after subtracting the separately estimated avoided costs of health care[159] and Social Security[160] if someone dies. We also subtract the "human capital" derived benefits of changes to lifetime earnings (LTE) and household production (HP), described elsewhere in this document. Thus, the general approach is:

$$(4.82) \quad VSLAdj = VSL - HC - SS - LTE - HP$$

WSIPP's VSL model is driven with the parameters shown in Exhibit 62, along with life table information displayed in Exhibit 61.

[155] For a general review of the analytical methods economists and others have used to assess the valuation of mortality risk, see W. I. Viscusi. (2008). *How to value a life* (Vanderbilt Law and Economics Research Paper No. 08-16), Nashville, TN: Vanderbilt University, Department of Economics.
[156] A recent review of the development of this research literature is provided in Cropper, M., Hammitt, J., & Robinson, L. (2011). *Valuing mortality risk reductions: Progress and challenges* (Working Paper No. 16971), Cambridge: National Bureau of Economic Research.
[157] Aldy, J. E. & Viscusi, W. K. (2008). Adjusting the value of a statistical life for age and cohort effects, *The Review of Economics and Statistics, 90*(3), 573-581.
[158] Hammitt J. K. & Haninger, K. (2010). Valuing fatal risks to children and adults: Effects of disease, latency, and risk aversion, J*ournal of Risk and Uncertainty, 40*(1), 57-83.
[159] To estimate health care costs by age for the average person in the population, we used data from the 2007 Medical Expenditure Panel Survey (MEPS), a nationally representative large-scale survey of American families, medical providers, and employers who report on healthcare service utilization and associated medical conditions, costs, and payments. An annual cost of services paid by public (e.g., Medicaid, Medicare), private (i.e., insurance), and personal (i.e., family out-of-pocket) sources, by age of person receiving those services, was computed for 2007 (the latest available year of the MEPS). These figures were adjusted for inflation and escalation in healthcare costs over time.
[160] We use an average Social Security payment of $14,154 in 2011 dollars, from age 65 on (Monthly Statistical Snapshot, April 2011, Social Security Administration). We escalate these dollars in future years using a 1.22% real growth rate, derived from the variable "Annual Scheduled Benefit Amounts for Retired Workers With Various Pre-Retirement Earnings Patterns Based on Intermediate Assumptions," Social Security 2011 Trustees Report, http://www.ssa.gov/OACT/TR/2011/lr6f10.html.

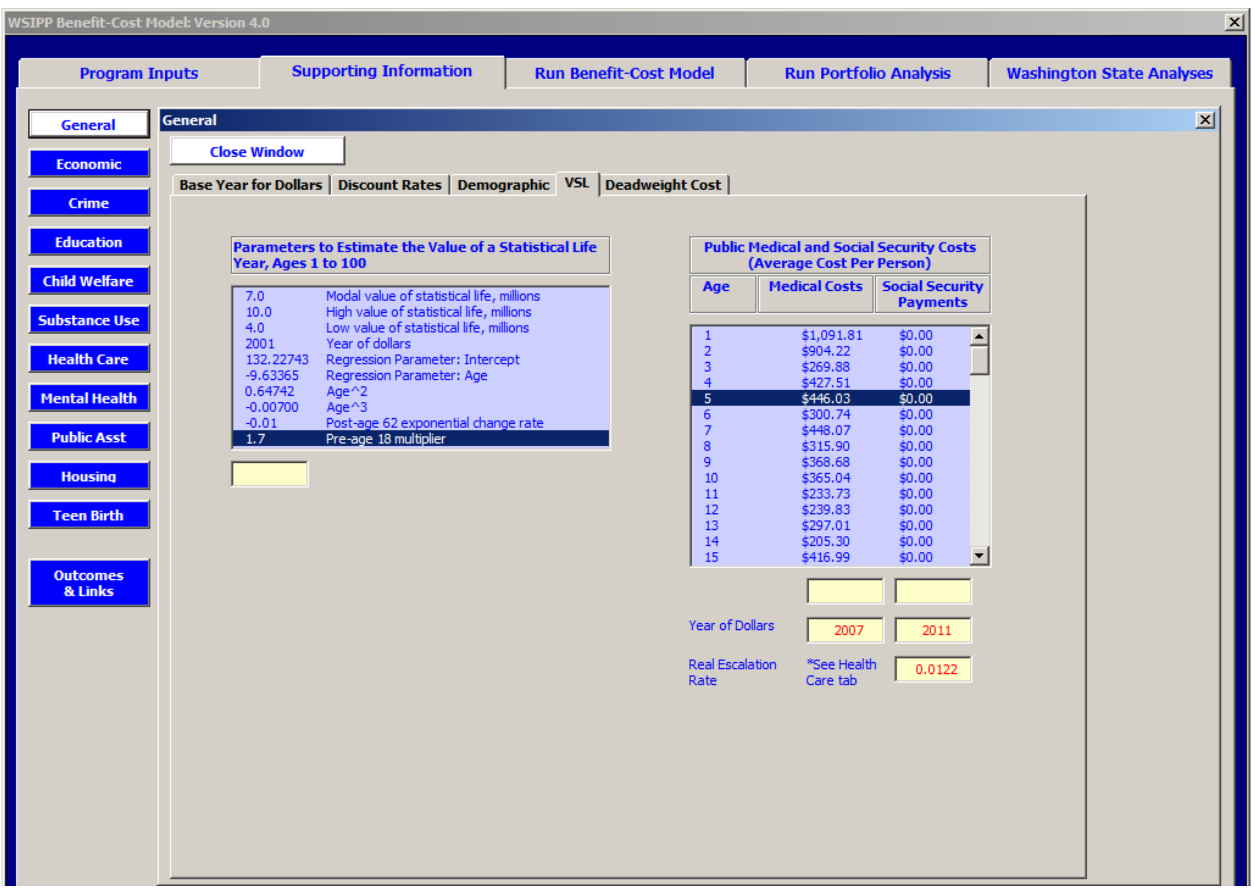
The user can specify a high, modal, and low value for VSL. These estimates are then modeled with a random draw from a triangular probability density distribution. For high and low VSL values, we use the preferred estimates reported in Kniesner et al. (2011).[161] For the modal value, we compute the average between the high and low. These values are expressed in year 2001 dollars, and the model updates these values with the Implicit Price Deflator for Personal Consumption Expenditures to the user-selected base year for the benefit-cost model.

The value of a statistical life year, $VSLY$, is then computed for the range of years considered in the Kniesner study (ages 18 to 62) with equation 4.83, where the discount rate selected by the user is $disrate$ and the average number of years of remaining life (for those currently 18 to 62) is taken from the general life table reported in Exhibit 61.

$$(4.83)\ VSLY = \frac{disrate \times VSL}{1-(1+disrate)^{-L}}$$

For example, with a $7 million VSL (in 2001 dollars), a 3% discount rate, and 41 years of remaining life, the $VSLY$ is $299,000 on average over the ages of 18 to 62. The next set of parameters in Exhibit 65 are used to distribute this average $VSLY$ value over the different years of a person's life. We use the estimates from Aldy and Viscusi (2008) to compute a third-order polynomial (the parameters are shown on the user input sheet). The Aldy and Viscusi analysis, using revealed preference data from labor market wages, estimates the annual $VSLY$ for ages 18 to 62. Thus, by applying the third order polynomial to the base value ($299,000) the following distributed estimates of $VSLY$ are obtained for ages 18 to 62.

Exhibit 62



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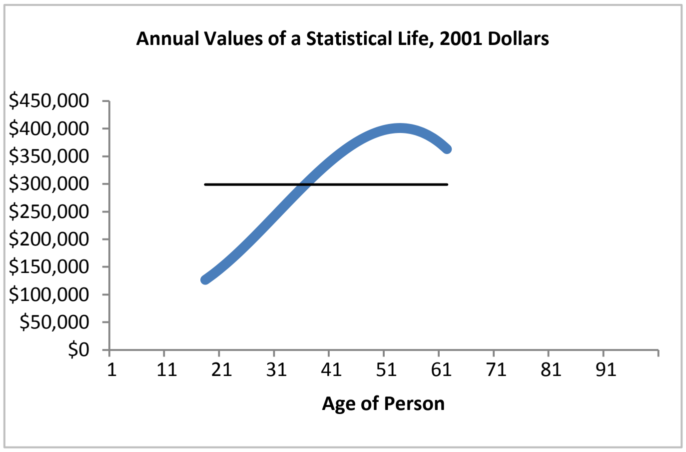
[161] Kniesner, T. J., Viscusi, W. K., & Ziliak, J. P. (2010). Policy relevant heterogeneity in the value of a statistical life: New evidence from panel data quantile regressions. *Journal of Risk and Uncertainty, 40*(1), 15-31.

Exhibit 63



The Aldy and Viscusi estimates only allow a distribution for ages 18 to 62. For ages older than 62, the empirical evidence is weak or non-existent. For these estimates, we follow the general approach taken by Viscusi and Hersch[162] (2008) and apply values for older ages based on the values for the last years (around age 60 to 62) for which estimates are available. The parameter in Exhibit 62 allows for an exponential rate of annual change that is multiplied by the age 62 value for $VSLY$. If zero is entered for the rate of change, then the $VSLY$ value for age 62 is applied for all ages to 100. Thus, for ages 63 to 100, VSLY is computed with:

$$(4.84)\quad VSLY_y = VSLY_{62} \times (1 + esc)^{(y-62+1)}$$

For ages less that 18 (the earliest age for which a $VSLY$ can be estimated with the Kniesner and Viscusi data), we use the ratio of VSL for children relative to adults reported in the stated preference paper by Hammitt and Haninger (2010). They found that the willingness to pay estimates for VSL for children are $12 to $15 million and $6 to $10 million for adults. We compute a point estimate for the ratio as 1.7 = (12 +15)/2 divided by (6 +10)/2. In the model, this ratio is applied to the average adult $VSLY$. Thus, for ages one to 18, $VSLY$ is computed with the Hammitt and Haninger ratio ($HHratio$):

$$(4.85)\quad VSLY_y = VSLY \times HHratio$$

[162] Viscusi, W. K. & Hersch, J. (2008). The mortality cost to smokers. *Journal of Health Economics, 27*(4), 943-958.

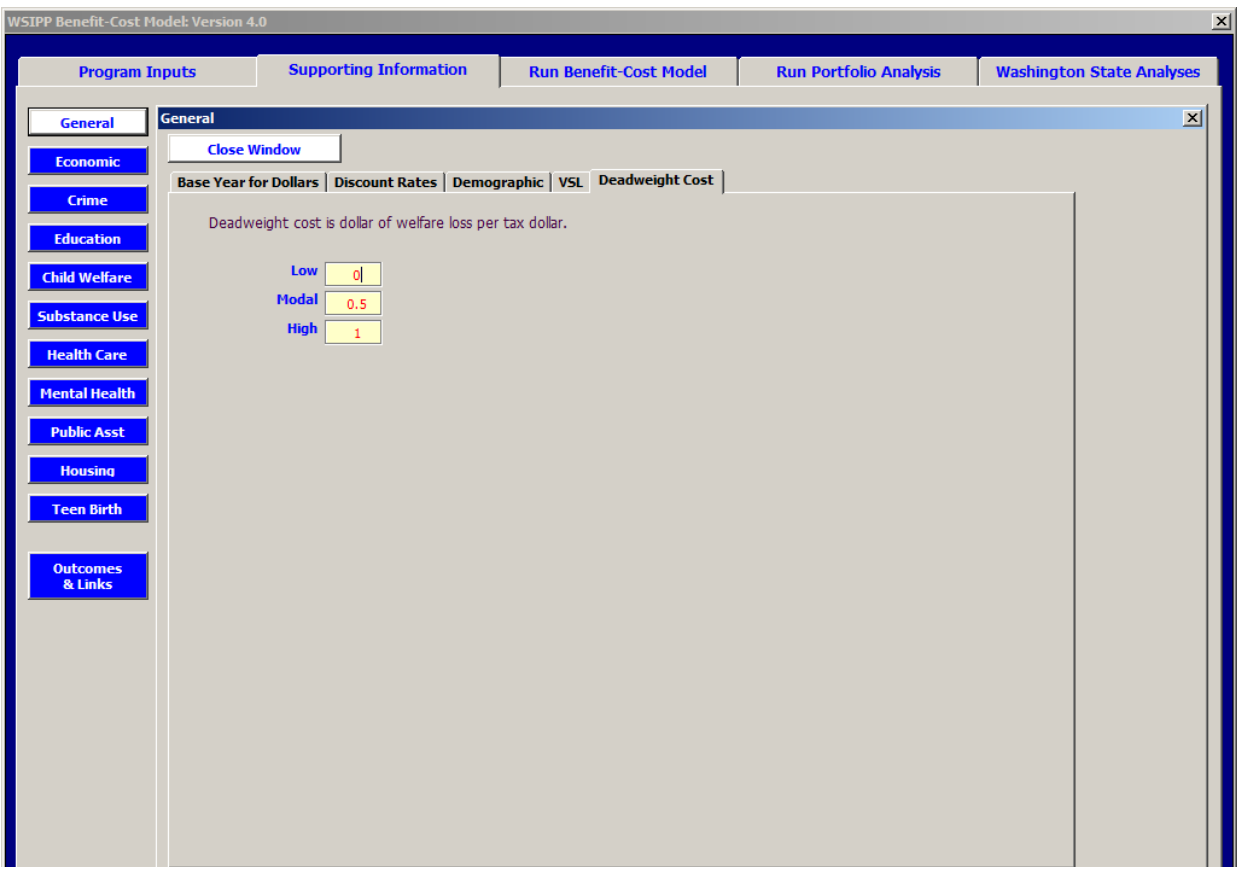
4.10e Deadweight Cost of Taxation

The model can compute estimates of the deadweight costs of taxation. The resulting values reflect the dollars of economic welfare loss per tax dollar raised to pay for program costs, or avoided if a program reduces taxpayer financed costs.[163] Because there is uncertainty around the appropriate values of deadweight costs, we model low, modal, and high multiplicative values. When the model is run in non-simulation mode, the modal deadweight value is used. In Monte Carlo simulation, each run randomly draws a deadweight value from a triangular probability density distribution, with the user-selected low, modal, and high deadweight values defining the triangle. The deadweight cost value is then multiplied by any tax-related cost or tax-related benefit of the program. The resulting net deadweight cost values are tallied and reported in the "Other Benefits" section of the output. For example, if a program costs taxpayers $1,000 per participant, and it is estimated that the program saves $600 in taxpayer savings from an improved outcome, e.g., less taxpayer spending on the criminal justice system, then with a modal deadweight cost value of 50%, there would be a net deadweight cost of the program of $200 ($600 times 50% minus $1,000 times 50%). In the actual run of the model, these calculations are carried out for each year of cash flows.

$$(4.86)\quad DWL_{age} = \sum_{y=age}^{N} \frac{(B_y - C_y) \times DWL\%}{(1+Dis)^y}$$

Exhibit 64 is a screen shot showing where the three deadweight cost values are entered. WSIPP uses a low real deadweight cost value of 0%, a modal rate of 50%, and a high rate of 100%. These input choices are the same values used by Heckman et al. (2010) in their analysis of the benefits and costs of the Perry Preschool program.[164] Also following Heckman et al. (2010), we do not apply any deadweight cost calculations estimated taxes from earnings outcomes.[165]

Exhibit 64

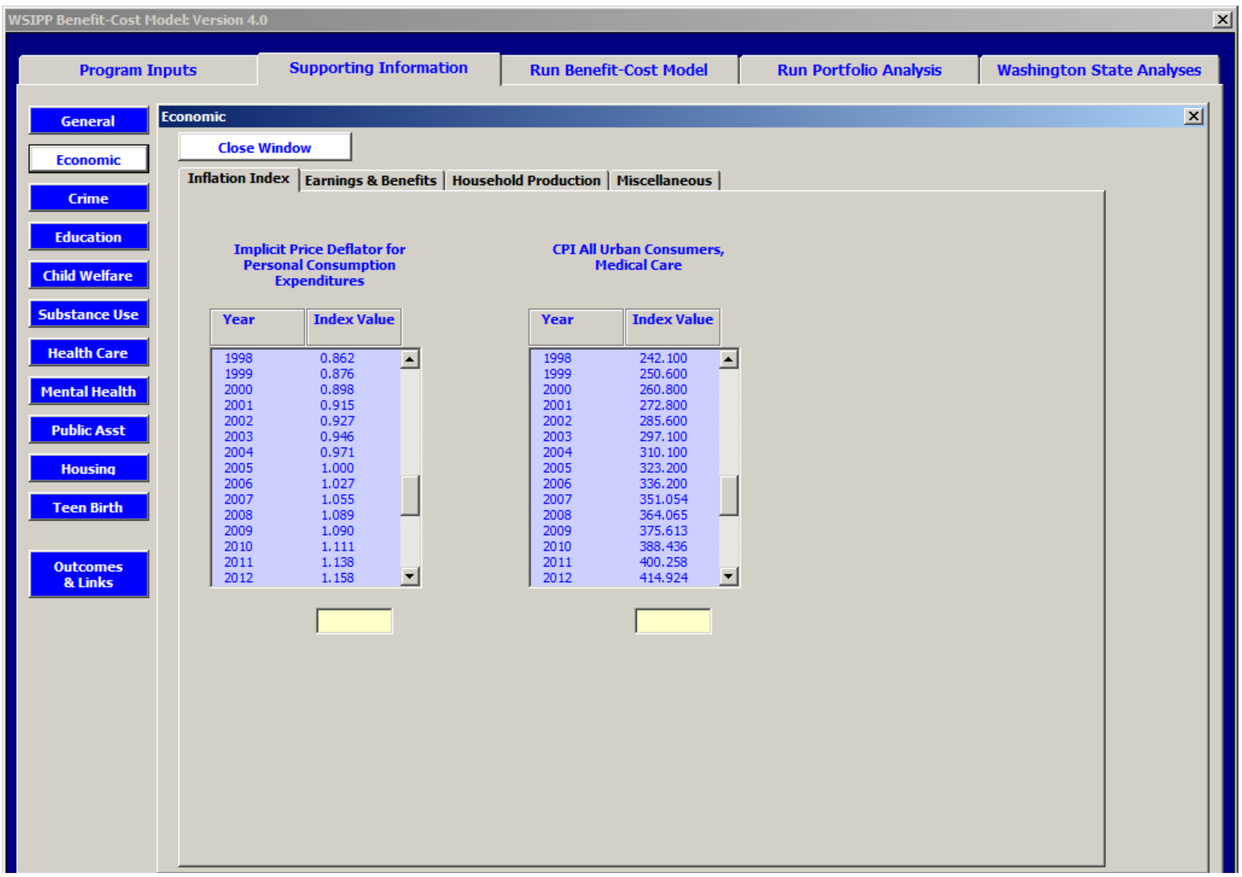


[163] Boardman, A. E., Greenberg, D. H., Vining, A. R., & Weimer, D. L. (1996). *Cost-benefit analysis: Concepts and practice* (4th ed). Upper Saddle River, NJ: Prentice Hall.
[164] Heckman et al. (2010).
[165] Heckman et al. (2010), see the Web Appendix to the Heckman study, Section J of the Appendix.

4.10f Inflation/Price Indexes

As noted, many of the monetary values in the model are denominated in different years' monetary units. The model coverts each of these to the base year chosen by the user. Exhibit 65 displays the input screen where the price indices used by the model are entered. The general inflation index used by WSIPP is United States Department of Commerce's Chain-Weighted Implicit Price Deflator for Personal Consumption Expenditures. The forecast years for the index is taken from the Washington State Economic and Revenue Forecast Council, the official forecasting agency for Washington State government. Since health care costs are central in WSIPP's benefit-cost model, and since health care prices have followed different paths than general prices, we also include a medical cost index, as shown in the Exhibit. We use the Medical Care Index of the Consumer Price Index for all urban consumers, published by the United State Department of Labor.

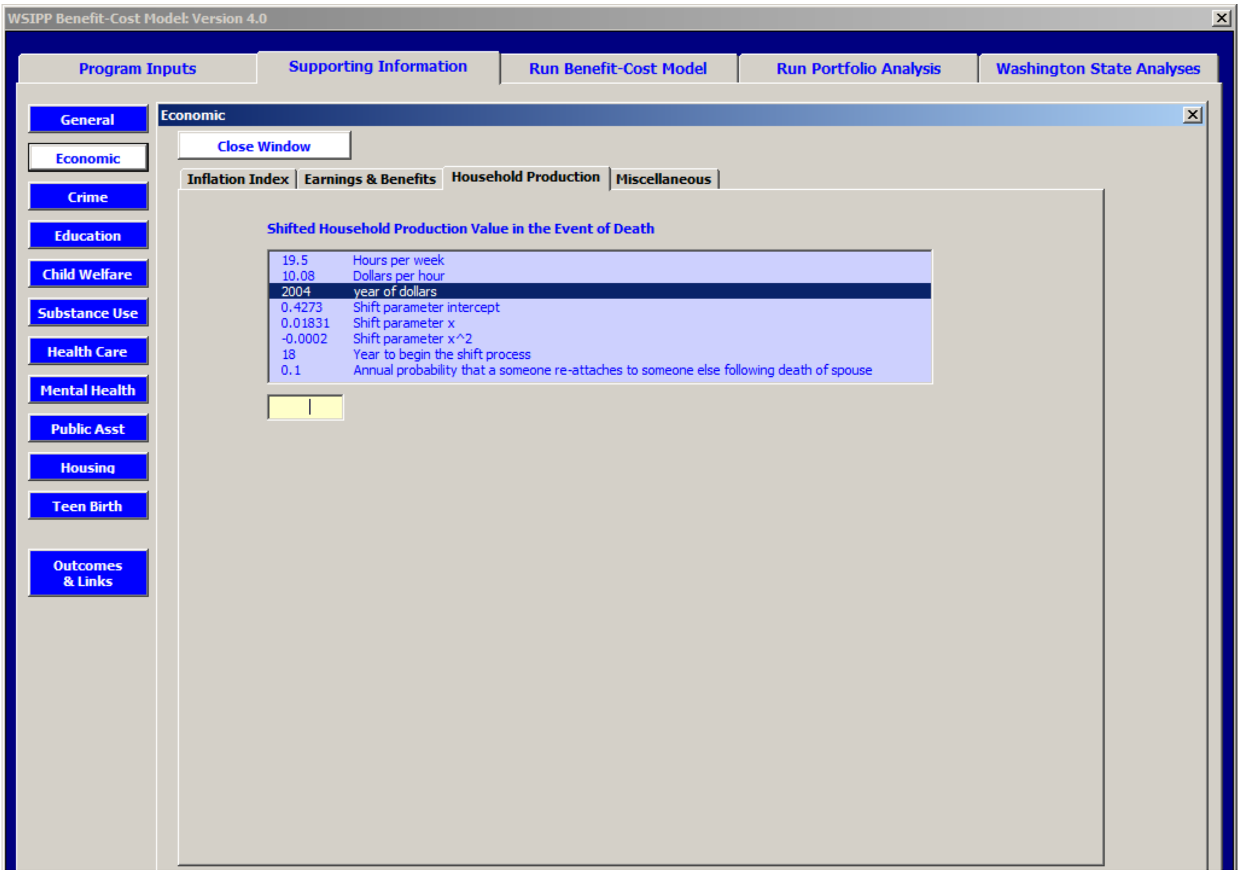
Exhibit 65



4.10g Household Production

In addition to the value of reduced or lost labor market value in the commercial economy, many studies of morbidity and mortality costs include estimates of the reduced or lost value of household production. We adopt that approach in this study. The model computes the value of lost household production that might be shifted to another in the event of death. Monetizing the value of household production is a common procedure in cost-of-illness studies.[166] We estimate 19.5 hours per week for household production. This estimate is based on an assumed 1.5 hours per day for housekeeping services, 1.0 hours per day for food preparation, and 2.0 hours per week for household maintenance. These estimates are quite close to the 21.4 hours per week calculated by Douglass et al.[167] The average shadow wage rate for these three household services was taken from United State Bureau of Labor Statistics data on average wage rates in Washington in 2004 for each service.[168]

Exhibit 66



To compute the household production effect for the incidence of the DSM disorders, we begin with the following equation:

$$(4.87) \quad H_a = HOURS * \$HOUR * 52 * \Pr SHIFT_a * INFLATION$$

[166] See, for example, Max, W., Rice, D., Sung, H., & Michel, M. (2004). *Valuing human life: Estimating the present value of lifetime earnings, 2000* (Paper PVLE2000). San Francisco: University of California, San Francisco. Retrieved June 30, 2011 from http://escholarship.org/uc/item/82d0550k#page-1

[167] Douglass, J., Kenney, G., & Miller, T. (1990). Which estimates of household production are best? *Journal of Forensic Economics, 4*(1), 25-45.

[168] Bureau of Labor Statistics. *November 2004 Occupational employment and wage estimates*. Retrieved June 30, 2011 from http://www.bls.gov/oes/current/oes_wa.htm#b39-0000

Not all of the value of lost household production will be shifted to others if a person dies or is disabled as a result of having an alcohol, drug, or mental health disorder. Some people live alone and no one else is required to assume the household production if the person becomes disabled or dies as a result of the disorder. We provide an estimate for this with the variable Pr*SHIFTa*, used in the previous equation. This variable provides an estimate of the probability that a person at age (*a*) will not be living alone and, if he or she becomes disordered, that the value of his or her household production will be shifted to someone else. We estimate this probability with national data from the same Bureau of Labor Statistics described above. The results of this estimation and are computed with this equation:

$$\text{(4.88)} \quad \Pr SHIFT_a = \frac{FHH_a}{(HH_a - GQ_a)}$$

The probability of shifting household production Pr*SHIFTa* in the event of a disorder is given by the total number of people in households with family members (*FHHa*) divided by the total number of people in households (*HHa*) (less those living in group quarters (*GQa*)). Values for all three variables come from the CPS.

The annual cash flows of lost household production associated with having a disorder of type *t* is estimated with the following equation:

$$\text{(4.89)} \quad \$HP_{ty} = \sum_{p}^{P} H_{p+y-1} * (1+ER)^{y-1} * EE_t * PP_{tp} * -1$$

In this equation, *$HPty* is the annual cash flow of shifted household production in year *y*, where *y* is the number of years following participation in a program.

4.10h Tax Rates

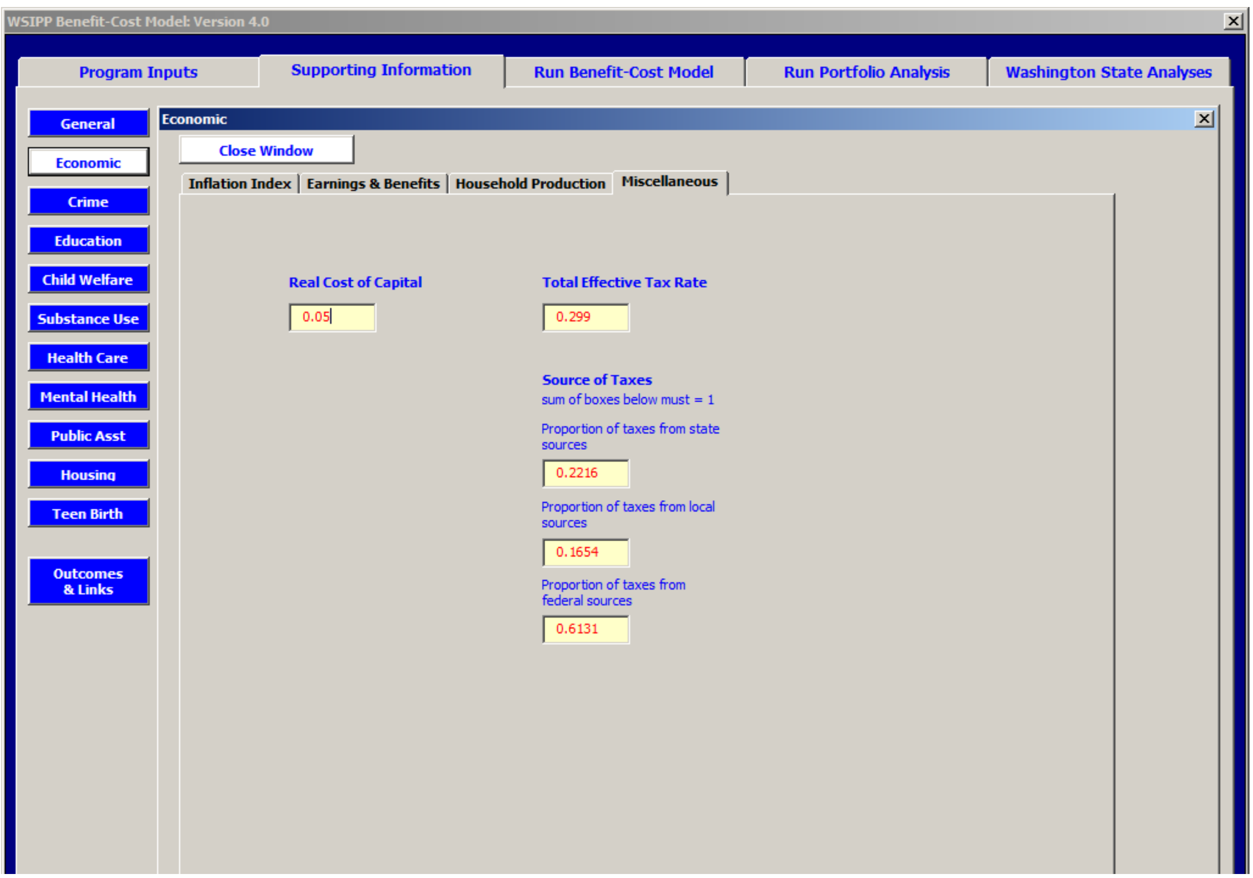
The benefit-cost model uses average tax rates[169] for several calculations. We used the aggregate total for Washington State from the Tax Foundation to represent a combination of all kinds (income, sales, property, and other) of taxes paid, as a percentage of income. This value is entered on the screen shot displayed in Exhibit 67.

In addition, we allow the user to input the ultimate sources of the tax rate, i.e., what proportion of taxes paid go to state, local and federal sources. We use nationally-based estimates from the Tax Policy Center[170] for those inputs.

4.10i Capital Costs

A few routines in the model use capital financing costs. The real cost of capital was obtained from discussions with fiscal staff of the Washington State legislature. This value is entered on the screen shot displayed in Exhibit 67.

Exhibit 67



[169] We looked at data from two separate sources: (1) McBride, W., Pomerleau, K, & Malm, E. (2013). *Tax Freedom Day® 2013: April 18, Five Days Later Than Last Year*. Washington, DC: Tax Foundation. Retrieved August 9, 2013 from: http://taxfoundation.org/sites/taxfoundation.org/files/docs/combinedtfd.pdf. (2) Citizens for Tax Justice (2013, April). Who Pays Taxes in America in 2013? Washington, DC: author. Retrieved August 9, 2013 from: http://www.ctj.org/pdf/taxday2013.pdf. The first source gave a federal estimate of a total effective tax rate of 29.3%, while the second source gave a nearly identical estimate of 30.1%. Because these numbers were so similar, we and the Tax Foundation also published separate estimates by state, we used the Washington State-specific estimate of 29.9% here.

[170] To breakdown total government receipts between federal, state, and local sources, we used estimates from the Tax Policy Center (a collaboration between the Urban Institute and the Brookings Institution). Retrieved July26, 2013 from: http://www.taxpolicycenter.org/briefing-book/background/numbers/revenue-breakdown.cfm.

Chapter 5: Meta Analyses of Linked Outcomes

5.1 Input Screen for Linked Outcome Effect Sizes

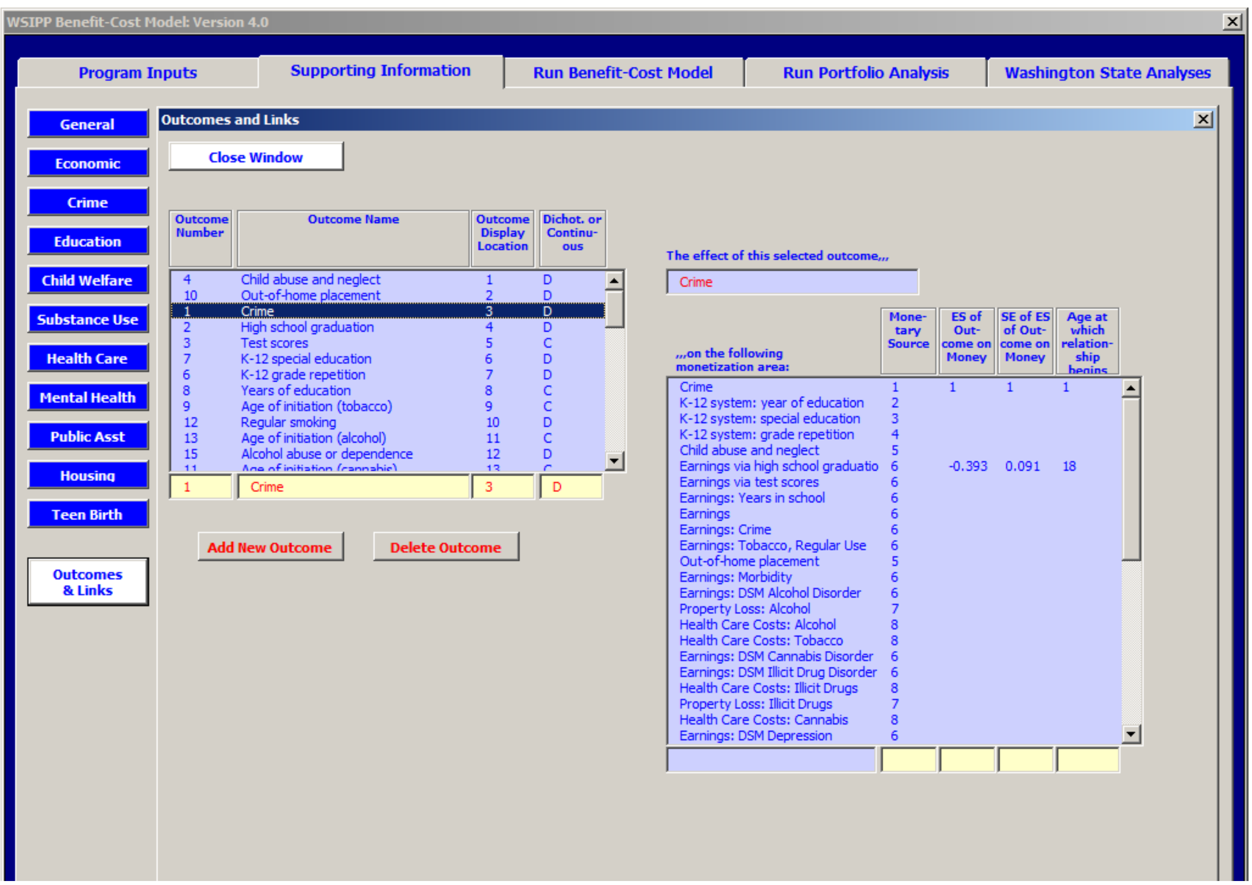
One of the features of WSIPP's benefit-cost model is its use of empirically established causal "links" between two outcomes. The logic follows this path: if a program evaluation establishes a causal effect of program P on outcome $O1$, and another body of research measures a causal relationship between outcome $O1$ and outcome $O2$, then it logically follows that P must have an effect on $O2$.

$$(5.1) \quad if\ P \rightarrow O1, \qquad and\ O1 \rightarrow O2, \quad then\ P \rightarrow O2$$

For example, if the juvenile justice program Functional Family Therapy (FFT) is shown to affect juvenile crime outcomes, and if separately analyzed longitudinal research establishes that juvenile crime is causally related to high school graduation probability, then FFT can be assumed to have an effect on high school graduation. Thus, while none of the outcome evaluations of in our meta-analytic review of FFT measure the effect of the program on high school graduation, it is reasonable to assume that there is a relationship between FFT and high school graduation since there is a separate body of research that demonstrates the linkage between juvenile crime and high school graduation.

The purpose of WSIPP's analyses of linked outcomes is to take advantage of this additional information. This is especially important in conducting benefit-cost analysis where the focus is on long-term effects from (usually) short-term program evaluations. Exhibit 68 displays a screen shot of where the linked effect size and standard error are entered. Exhibit 69 displays WSIPP's current meta-analytic results of the linkage literature, and Exhibit 70 lists the individual studies that were meta-analyzed to establish the causal estimates.

Exhibit 68



5.2 WSIPP Adjustments to Effect Sizes

In the last two columns of Exhibit 69 we list the “adjusted effect size” and standard error that we use in our analyses. As we do with the results from program evaluations (see Chapter 2.3), we make adjustments to the initial effect sizes to account for various forms of unobserved heterogeneity that we suspect exists in the underlying studies. We make three types of adjustments that we deem to be necessary to increase our confidence in the evidence for a causal relationship between two outcomes. We make adjustments for (1) the methodological quality of each study we include in the meta-analyses; (2) the degree to which findings for a particular sample of people can be generalized to other populations; and (3) the relevance of the independent and dependent measures that individual studies examined.

5.2a Methodological Quality

As we do with the program evaluation literature, we also apply weights to studies to account for expected biases that probably exist in certain types of research designs. To establish that one outcome leads to another, longitudinal studies that establish temporal ordering—that a first outcome (e.g., juvenile crime) precedes another outcome (e.g., high school graduation)—and include measures of other factors that also influence the outcome of interest are preferred. Ideally, the study would statistically control for both observable factors—e.g., family income—and unobservable variables by using fixed effects modeling, natural experiments, twin studies, instrumental variables, or other techniques. Other studies may be cross-sectional or may not statistically control for as many other potentially confounding factors; this does not mean that results from these studies are of no value, but it does mean that less confidence can be placed in any cause-and-effect conclusions drawn from the results.

To account for the differences in the quality of research designs, we use a 6-point scale (with values ranging from zero to five) as a way to adjust the reported results. On this scale, a rating of 95 reflects a study in which the most confidence can be placed: a longitudinal study with temporal ordering and good controls for observable and unobservable confounds. A rating of 90 reflects a study in which temporal ordering is not established and we cannot infer a causal link between independent and dependent variables.

On the 90-to-95 scale as interpreted by WSIPP, each study is rated as follows:

- A 95 is assigned to a longitudinal study with temporal ordering and good statistical controls for observable AND unobservable confounds.
- A 94 is assigned to a longitudinal study with temporal ordering and good statistical controls for observable confounds.
- A 93 is assigned to a longitudinal study with temporal ordering and not as many controls.
- A 92 is assigned to a cross-sectional study with temporal ordering, and retrospective measurement.
- A 91 is a placeholder rating that is not currently used.
- A 90 involves a study for which we cannot infer causal link between independent and dependent variables.

In our meta-analyses, we do not use the results from studies rated as a 90 or 91 on this scale.

An explicit adjustment factor is assigned to the results of individual effect sizes based on WSIPP’s judgment concerning research design quality. This adjustment is critical and the only practical way to combine the results from high quality studies (e.g., a level 95 study) with those of lesser design quality (level 94 and lower studies). The effect of the adjustment is to multiply the effect size for any study by the appropriate research design factor. For example, if a study has an effect size of -0.20 and it is deemed a level 4 study, then the -0.20 effect size would be multiplied by 0.75 to produce a -0.15 adjusted effect size for use in the analysis. In Exhibit 70, the column labeled “research design” indicates the multiplier applied to each study’s results used in the meta-analyses.

5.2b Generalizability of the Sample

We also adjust the effect sizes for linked outcomes for the degree to which the individuals included in the study sample are representative of the population as a whole. If we determine that a sample is not representative of the Washington State population, we use a multiplicative factor of 0.75 to adjust the effect size downward.

5.2c Relevance of the Independent and Dependent Variables

Some studies use outcome measures that may not be precise gauges of the way the benefit-cost model monetizes results. In these cases, we record a flag that can later be used to adjust the effect. For example, the benefit-cost model monetizes disordered alcohol use based on a DSM-level alcohol disorder. If a longitudinal study measures a linkage between “heavy drinking” (but not DSM alcohol use) and employment, then we will flag this weaker measure. In these cases, we adjust the effect sizes by set factors.

Exhibit 69
Linked Outcomes
Meta-Analytic Estimates of Standardized Mean Difference Effect Sizes

Estimated Causal Links Between Outcomes	Topic Reference Number	Number of Effect Sizes	Meta-Analytic Results Before Adjusting Effect Sizes: Fixed Effects Model: Weighted Mean Effect Size & p-value			Homogeneity Test (p-value to reject homogeneity)		Random Effects: Weighted Mean Effect Size & p-value			Adjusted Effect Size and Standard Error Used in the Benefit-Cost Analysis	
			ES	SE	p-value	Q-stat	p-value	ES	SE	p-value	ES	SE
Child Abuse & Neglect, leading to…												
High school graduation	1	5	-.412	0.048	0.000	14.31	0.006	-.404	0.098	0.000	**-.212**	**0.098**
Special education	5	1	.389	0.036	0.000	0.00	na				**.194**	**0.036**
Test scores-academic	2	3	-.248	0.052	0.000	0.86	0.649	-.248	0.052	0.000	**-.099**	**0.052**
Alcohol (disordered use)	3	5	.163	0.028	0.000	3.08	0.545	.163	0.028	0.000	**.055**	**0.028**
Illicit drugs (disordered use)	4	5	.279	0.061	0.000	2.21	0.697	.279	0.061	0.000	**.200**	**0.061**
Depression	6	7	.289	0.029	0.000	16.81	0.010	.257	0.053	0.000	**.095**	**0.053**
Teen births <18	7	2	.200	0.113	0.076	7.26	0.007	.431	0.403	0.285	**.175**	**0.403**
Any crime measure	8	12	.503	0.027	0.000	56.45	0.000	.513	0.069	0.000	**.254**	**0.069**
Alcohol Disorder, leading to…												
Any crime measure	11	6	.237	0.017	0.000	204.26	0.000	.262	0.124	0.035	**.134**	**0.124**
Employment	12	13	-.514	0.012	0.000	1228.76	0.000	-.464	0.128	0.000	**-.210**	**0.128**
Earnings/Wages	13	9	-.082	0.012	0.000	30.45	0.000	-.065	0.025	0.009	**-.048**	**0.025**
Illicit Drug Disorder, leading to…												
Employment	14	5	-.211	0.026	0.000	3.18	0.528	-.211	0.026	0.000	**-.126**	**0.026**
Earnings/Wages	15	2	-.048	0.033	0.149	27.82	0.000	-.333	0.343	0.333	**.000**	**0.000**
Any crime measure	16	1	.250	0.100	0.013	0.00	na				**.187**	**0.100**
Cannabis use, leading to…												
High school graduation	17	13	-.205	0.012	0.000	71.48	0.000	-.286	0.038	0.000	**-.211**	**0.038**
Smoking, leading to…												
Employment	18	2	-.037	0.009	0.000	19.16	0.000	-.083	0.062	0.177	**-.062**	**0.062**
Earnings/Wages	19	5	-.040	0.006	0.000	247.68	0.000	-.128	0.067	0.056	**-.067**	**0.067**
Mental Health Disorder, leading to…												
Employment (DSM MI)	27	18	-.409	0.007	0.000	883.94	0.000	-.406	0.059	0.000	**-.197**	**0.059**
Earnings/Wages (DSM MI)	28	9	-.081	0.007	0.000	35.73	0.000	-.095	0.020	0.000	**-.060**	**0.020**
Employment (Depression)	29	10	-.314	0.018	0.000	80.59	0.000	-.349	0.060	0.000	**-.174**	**0.060**
Earnings/Wages (Depression)	30	4	-.043	0.020	0.028	1.95	0.582	-.043	0.020	0.028	**-.030**	**0.020**
Employment (Anxiety disorder)	31	7	-.141	0.019	0.000	57.47	0.000	-.231	0.068	0.001	**-.110**	**0.068**
Earnings/Wages (Anxiety disorder)	32	3	-.205	0.027	0.000	35.14	0.000	-.187	0.116	0.108	**-.126**	**0.116**
Any crime measure (Externalizing composite)	33	12	.316	0.027	0.000	26.24	0.006	.334	0.048	0.000	**.230**	**0.048**
High school graduation (Externalizing composite)	34	17	-.323	0.015	0.000	36.65	0.002	-.343	0.028	0.000	**-.229**	**0.028**
High school graduation (Internalizing composite)	35	11	-.091	0.016	0.000	24.25	0.007	-.113	0.034	0.001	**-.066**	**0.034**
Grade retention (ADHD)	36	4	.466	0.048	0.000	3.02	0.388	.466	0.049	0.000	**.321**	**0.049**
Test scores-academic (ADHD)	37	3	-.370	0.039	0.000	14.09	0.001	-.375	0.102	0.000	**-.282**	**0.102**
High school graduation (ADHD)	38	6	-.301	0.023	0.000	1.90	0.863	-.301	0.023	0.000	**-.213**	**0.023**
Any crime measure (ADHD)	39	5	.273	0.039	0.000	17.37	0.002	.316	0.096	0.001	**.168**	**0.096**
High school graduation (Conduct Disorder)	40	7	-.426	0.028	0.000	9.58	0.144	-.443	0.045	0.000	**-.277**	**0.045**
Any crime measure (Conduct Disorder)	41	7	.355	0.037	0.000	6.54	0.365	.356	0.041	0.000	**.275**	**0.041**
Any crime measure (Schiz. or Bipolar, Inpatient)	42	3	.525	0.029	0.000	114.70	0.000	.529	0.263	0.044	**.265**	**0.263**

Exhibit 69, continued

Estimated Causal Links Between Outcomes	Topic Reference Number	Number of Effect Sizes	Meta-Analytic Results Before Adjusting Effect Sizes: Fixed Effects Model: Weighted Mean Effect Size & p-value			Fixed Effects Model: Homogeneity Test (p-value to reject homogeneity)		Random Effects: Weighted Mean Effect Size & p-value			Adjusted Effect Size and Standard Error Used in the Benefit-Cost Analysis	
			ES	SE	p-value	Q-stat	p-value	ES	SE	p-value	ES	SE
Teen Birth (< 18 years old), leading to…												
Child abuse and neglect (Births < 18, child)	20	1	.238	0.008	0.000	0.00	na				**.119**	**0.008**
Out-of-home placements (Births < 18, child)	21	1	.116	0.013	0.000	0.00	na				**.058**	**0.013**
Grade retention (Births < 18, child)	23	4	.205	0.033	0.000	2.03	0.567	.205	0.033	0.000	**.202**	**0.033**
Any crime measure (Births < 18, child)	26	2	.183	0.068	0.007	0.70	0.403	.183	0.068	0.007	**.137**	**0.068**
High school graduation (Births < 18, child)	24	3	-.213	0.068	0.002	0.84	0.657	-.213	0.068	0.002	**-.127**	**0.068**
Public Assistance (Births < 18, mother)	22	3	.173	0.096	0.072	4.65	0.098	.244	0.164	0.138	**.145**	**0.164**
High school graduation (Births < 18, mother)	25	4	-.181	0.072	0.013	0.79	0.852	-.181	0.072	0.013	**-.155**	**0.072**
High School Graduation, leading to…												
Any crime measure	10	11	-.150	0.008	0.000	100.06	0.000	-.215	0.030	0.000	**-.143**	**0.030**
Crime, leading to…												
High school graduation	9	6	-.469	0.032	0.000	33.91	0.000	-.496	0.091	0.000	**-.393**	**0.091**

Exhibit 70

Individual Effect Sizes Used in the Meta-Analysis of Each Topic											
			Study Results				Multiplicative Weights & Adjusted Effect Size				
Study (Date)	Topic Number	Un-adjusted effect size	Number in test condition group	Number in control group	Inverse variance weight-fixed effects	Inverse variance weight-random effects	Re-search design	General-izability of sample	Relevance of inde-pendent variable measure	Relevance of de-pendent variable measure	Adjusted effect size
Thornberry et al., 2001	1	-0.176	134	604	45.9	18.2	0.75	1.00	1.00	1.00	-0.132
McGloin & Widom, 2001	1	-0.479	676	520	185.5	25.8	0.50	1.00	1.00	1.00	-0.240
Lansford et al., 2007	1	-0.854	69	505	34.5	16.0	0.75	1.00	0.50	1.00	-0.320
Boden et al., 2007	1	-0.158	171	800	64.5	20.5	0.75	1.00	0.50	1.00	-0.059
Mersky & Topitzes, 2010	1	-0.407	179	1148	99.5	23.1	0.75	1.00	1.00	1.00	-0.305
Lansford et al., 2002	2	-0.145	50	387	44.2	44.2	0.75	1.00	0.50	1.00	-0.054
Slade & Wissow, 2007	2	-0.286	632	1146	209.6	209.6	1.00	1.00	0.50	0.50	-0.071
Topitzes et al., 2010	2	-0.220	135	990	118.5	118.5	0.75	1.00	1.00	1.00	-0.165
Fergusson & Lynskey, 1997	3	0.409	118	111	23.9	23.9	0.50	1.00	0.50	1.00	0.102
Scott et al., 2010	3	0.200	221	1923	47.6	47.6	0.50	1.00	1.00	1.00	0.100
Thornberry et al., 2010	3	0.171	170	645	134.2	134.2	0.75	1.00	1.00	1.00	0.129
Horwitz et al., 2001	3	0.075	637	510	192.3	192.3	0.50	1.00	1.00	1.00	0.038
Shin et al., 2009	3	0.173	6729	6019	851.9	851.9	0.50	1.00	0.50	1.00	0.043
Fergusson & Lynskey, 1997	4	0.176	118	111	15.7	15.7	0.50	1.00	0.50	1.00	0.044
Scott et al., 2010	4	0.417	221	1923	31.5	31.5	0.50	1.00	1.00	1.00	0.208
Thornberry et al., 2010	4	0.275	170	645	133.7	133.7	0.75	1.00	1.00	1.00	0.206
Fergusson et al., 2008	4	0.113	162	839	38.9	38.9	0.50	1.00	0.50	1.00	0.028
Arteaga et al., 2010	4	0.367	117	1091	48.6	48.6	1.00	1.00	1.00	1.00	0.367
Jonson-Reid et al., 2004	5	0.389	3987	3953	767.9	767.9	0.50	1.00	1.00	1.00	0.194
Chapman et al., 2004	6	0.411	2373	7087	511.7	72.4	0.50	1.00	0.50	1.00	0.103
Widom et al., 2007	6	0.145	676	520	139.3	52.5	0.50	1.00	1.00	1.00	0.072
Scott et al., 2010	6	0.366	221	1923	59.2	34.8	0.50	1.00	1.00	1.00	0.183
Thornberry et al., 2010	6	0.158	170	645	134.3	51.8	0.75	1.00	1.00	1.00	0.118
Fletcher, 2009	6	0.297	182	3840	80.4	41.2	1.00	1.00	0.50	1.00	0.148
Springer et al., 2007	6	0.156	234	1817	207.0	59.9	0.50	1.00	0.50	0.50	0.020
Fergusson et al., 2008	6	0.266	162	839	76.5	40.1	0.50	1.00	0.50	1.00	0.067
Widom & Kuhns, 1996	7	0.063	338	244	65.4	3.4	0.75	1.00	1.00	1.00	0.047
Noll et al., 2003	7	0.873	77	89	13.3	2.8	0.50	0.75	1.00	1.00	0.327
Cohen et al., 2004	8	0.733	51	611	30.5	14.0	0.50	1.00	0.50	1.00	0.183
Maxfield & Widom, 1996	8	0.272	908	667	253.0	23.4	0.50	1.00	1.00	1.00	0.136
English et al., 2002	8	0.600	877	877	235.6	23.2	0.50	1.00	1.00	0.50	0.150
Stouthamer-Loeber et al., 2001	8	0.379	52	104	23.1	12.2	0.50	1.00	1.00	1.00	0.190
Fergusson & Lynskey, 1997	8	0.340	118	111	13.7	8.9	0.50	1.00	0.50	1.00	0.085
Currie & Tekin, 2006	8	0.494	3121	10388	414.1	24.2	1.00	1.00	0.50	1.00	0.247
Lansford et al., 2007	8	0.084	69	505	37.7	15.3	0.75	1.00	0.50	1.00	0.031
Mersky & Reynolds, 2007	8	0.451	129	1275	49.3	16.9	0.75	1.00	1.00	1.00	0.338
Lemmon, 1999	8	1.083	267	365	79.8	19.5	0.50	0.75	1.00	1.00	0.406
Stouthamer-Loeber et al., 2002	8	0.635	83	140	28.3	13.5	0.75	1.00	1.00	1.00	0.476
Thornberry et al., 2010	8	0.342	170	645	82.6	19.6	0.75	1.00	1.00	1.00	0.257
Van Dorn, et al., 2011	8	0.620	3465	31188	161.4	22.2	0.75	1.00	1.00	1.00	0.465
Hjalmarsson, 2008	9	-0.183	467	6950	263.1	23.9	1.00	1.00	1.00	1.00	-0.183
Tanner et al., 1999	9	-0.403	478	1882	130.9	21.9	0.75	1.00	1.00	1.00	-0.302
Hirschfield, 2009	9	-0.666	216	2039	31.6	14.4	0.75	1.00	1.00	1.00	-0.500
Apel & Sweeten, 2009	9	-0.621	400	4649	233.4	23.6	0.75	1.00	1.00	1.00	-0.466
Webbink et al., 2008	9	-0.588	1126	1126	318.1	24.3	1.00	1.00	1.00	1.00	-0.588
Kirk & Sampson, 2009	9	-0.637	76	102	26.4	13.2	0.50	1.00	1.00	1.00	-0.319
Lochner & Moretti, 2004	10	-0.083	16319	16319	8152.7	127.8	1.00	1.00	1.00	1.00	-0.083
Lochner & Moretti, 2004	10	-0.458	1724	978	287.7	89.5	0.50	1.00	1.00	1.00	-0.229

Exhibit 70

Individual Effect Sizes Used in the Meta-Analysis of Each Topic											
		Study Results					Multiplicative Weights & Adjusted Effect Size				
Study (Date)	Topic Number	Un-adjusted effect size	Number in test condition group	Number in control group	Inverse variance weight-fixed effects	Inverse variance weight-random effects	Re-search design	General-izability of sample	Relevance of inde-pendent variable measure	Relevance of de-pendent variable measure	Adjusted effect size
Levitt & Lochner, 2001	10	-0.144	2135	2153	706.9	109.7	0.50	1.00	1.00	1.00	-0.072
Sabates, 2008	10	-0.200	9781	9781	4866.2	126.5	0.50	1.00	1.00	1.00	-0.100
Buonanno & Leonida, 2009	10	-0.176	1600	1600	796.9	111.6	0.50	1.00	1.00	1.00	-0.088
Ou & Reynolds, 2010	10	-0.239	374	359	118.9	62.1	0.75	1.00	1.00	1.00	-0.179
Machin et al., 2011	10	-0.211	839	839	417.0	99.0	0.75	1.00	1.00	1.00	-0.158
Brugard & Falch, 2011	10	-0.282	34914	16716	692.5	109.3	0.75	1.00	1.00	1.00	-0.212
Webbink et al., 2008	10	-0.186	1125	1125	98.3	56.0	1.00	1.00	1.00	1.00	-0.186
Bjerk, 2011	10	-0.293	1286	672	437.1	100.1	0.75	1.00	1.00	1.00	-0.220
Van Dorn, et al., 2011	10	-0.158	28987	5666	528.0	104.2	0.75	1.00	1.00	1.00	-0.119
Fergusson & Horwood, 2000	11	0.283	262	749	192.6	10.8	1.00	1.00	0.50	1.00	0.141
Lipsey et al., 1997	11	0.371	375	1500	103.6	10.3	0.50	1.00	1.00	1.00	0.185
Elbogen & Johnson, 2009	11	0.150	7353	27300	435.2	11.1	0.75	1.00	0.50	1.00	0.056
Carpenter, 2007	11	0.025	4600	4600	1562.3	11.3	1.00	1.00	0.50	1.00	0.013
WSIPP analysis	11	0.599	4431	33147	978.2	11.3	0.50	1.00	1.00	1.00	0.299
Van Dorn, et al., 2011	11	0.145	3465	31188	86.2	10.1	0.75	1.00	1.00	1.00	0.109
Zuvekas et al., 2005	12	-0.068	2887	6933	484.5	4.8	0.50	1.00	1.00	1.00	-0.034
Mullahy & Sindelar, 1996	12	-0.407	2381	21425	1294.3	4.8	0.50	1.00	1.00	1.00	-0.204
Terza, 2002	12	-1.042	982	8840	487.5	4.8	0.50	1.00	1.00	0.50	-0.260
Chevrou-Severac & Jeanrenaud, 2002	12	-0.613	216	7283	49.6	4.4	0.50	1.00	1.00	0.50	-0.153
Feng et al., 2001	12	0.044	647	7475	241.9	4.7	0.75	1.00	1.00	0.50	0.016
Auld, 2002	12	-0.602	982	8840	387.1	4.7	0.50	1.00	1.00	0.50	-0.150
MacDonald & Shields, 2004	12	-0.217	664	5980	298.8	4.7	0.50	1.00	1.00	0.50	-0.054
Cook & Peters, 2005	12	-0.036	624	7432	381.0	4.7	1.00	1.00	1.00	0.50	-0.018
Saffer & Dave, 2005	12	-0.082	210	6790	125.9	4.6	1.00	1.00	1.00	0.50	-0.041
Johansson et al, 2007	12	-1.161	453	4298	216.0	4.7	0.50	0.75	1.00	1.00	-0.435
French et al., 2011	12	-0.211	3819	36917	963.0	4.8	0.75	1.00	1.00	1.00	-0.158
Sangchai, 2006	12	-0.371	1689	16339	659.0	4.8	0.75	1.00	1.00	1.00	-0.278
Sangchai, 2006	12	-1.265	2273	21552	1018.1	4.8	0.75	1.00	1.00	1.00	-0.949
Zarkin et al., 1998	13	-0.004	442	11683	425.9	160.0	0.50	1.00	1.00	0.50	-0.001
Kenkel & Ribar, 1994	13	-0.172	1742	5346	1310.4	214.4	1.00	1.00	1.00	1.00	-0.172
Bray, 2005	13	-0.017	277	1572	235.7	122.8	1.00	1.00	1.00	0.50	-0.009
Jones & Richmond, 2006	13	-0.051	798	2848	622.9	181.6	0.75	1.00	1.00	1.00	-0.038
Renna, 2008	13	-0.080	578	3548	496.5	169.0	1.00	1.00	1.00	1.00	-0.080
Barrett, 2002	13	-0.118	1104	4601	889.4	199.0	0.50	1.00	1.00	0.50	-0.029
Keng & Huffman, 2010	13	-0.119	1393	2707	918.4	200.4	1.00	1.00	1.00	0.50	-0.060
Peters, 2004	13	-0.048	1930	6842	1505.0	219.0	1.00	1.00	1.00	0.50	-0.024
Auld, 2005	13	0.104	362	3529	328.1	143.9	0.50	1.00	0.50	1.00	0.026
Buchmueller & Zuvekas, 1998	14	-0.220	449	1651	178.8	178.8	0.50	1.00	1.00	1.00	-0.110
Zuvekas et al., 2005	14	-0.171	929	8089	226.9	226.9	0.50	1.00	1.00	1.00	-0.086
Alexandre & French, 2004	14	-0.285	926	553	226.1	226.1	0.75	1.00	1.00	1.00	-0.214
French et al., 2001	14	-0.271	379	9242	216.0	216.0	0.75	1.00	1.00	1.00	-0.204
WSIPP analysis	14	-0.176	990	37077	640.8	640.8	0.50	1.00	1.00	1.00	-0.088
Zuvekas et al., 2005	15	0.000	929	8089	833.2	4.4	0.50	1.00	1.00	1.00	0.000
Ringel et al., 2006	15	-0.687	71	721	63.4	4.1	0.50	1.00	1.00	1.00	-0.343
Van Dorn, et al., 2011	16	0.250	3465	31188	99.8	99.8	0.75	1.00	1.00	1.00	0.187
Bray et al., 2000	17	-0.508	630	762	111.1	48.4	0.75	1.00	1.00	1.00	-0.381
Ellickson et al., 1998	17	-0.074	860	3530	228.8	62.5	0.75	1.00	1.00	1.00	-0.056
Mensch & Kandel, 1988	17	-0.177	7567	4094	1317.0	80.7	0.75	1.00	1.00	1.00	-0.132

Exhibit 70

Individual Effect Sizes Used in the Meta-Analysis of Each Topic											
			Study Results				Multiplicative Weights & Adjusted Effect Size				
Study (Date)	Topic Number	Un-adjusted effect size	Number in test condition group	Number in control group	Inverse variance weight-fixed effects	Inverse variance weight-random effects	Re-search design	General-izability of sample	Relevance of inde-pendent variable measure	Relevance of de-pendent variable measure	Adjusted effect size
Yamada et al., 1996	17	-0.432	75	597	17.1	14.3	0.50	1.00	1.00	1.00	-0.216
Fergusson & Horwood, 1997	17	-0.385	180	755	73.9	39.7	1.00	0.75	1.00	1.00	-0.289
Brook et al., 2002	17	-0.217	100	1048	61.9	36.0	0.75	1.00	1.00	1.00	-0.162
McCaffrey et al., 2010	17	-0.112	276	2482	27.8	21.0	0.75	1.00	1.00	1.00	-0.084
van Ours & Williams, 2009	17	-0.198	5931	5862	1994.5	82.4	0.50	1.00	1.00	1.00	-0.099
Horwood et al., 2010	17	-0.476	420	624	155.1	55.3	1.00	0.75	1.00	1.00	-0.357
Horwood et al., 2010	17	-0.185	482	1036	121.0	50.2	1.00	1.00	1.00	1.00	-0.185
Horwood et al., 2010	17	-0.480	1418	2176	337.6	68.5	1.00	1.00	1.00	1.00	-0.480
Ensminger et al., 1996	17	-0.621	109	456	53.8	33.1	0.75	0.75	1.00	1.00	-0.349
WSIPP analysis	17	-0.152	10890	13748	2235.8	82.7	0.50	1.00	1.00	1.00	-0.076
Jofre-Bonet et al., 2005	18	-0.024	31105	88778	12150.8	137.6	0.75	1.00	1.00	1.00	-0.018
Dastan, 2011	18	-0.147	4203	7806	1411.0	126.7	0.75	1.00	1.00	1.00	-0.110
Anger & Kvasnicka, 2010	19	0.000	819	1149	478.2	41.9	0.50	1.00	1.00	1.00	0.000
Auld, 2005	19	-0.579	1280	2611	828.3	43.6	0.50	1.00	1.00	1.00	-0.289
Jofre-Bonet et al., 2005	19	-0.026	31105	88778	23033.1	45.9	0.75	1.00	1.00	1.00	-0.019
Dastan, 2011	19	-0.029	4203	7806	2731.8	45.2	0.75	1.00	1.00	1.00	-0.022
Braakmann, 2008	19	-0.015	3611	8647	2547.2	45.2	0.50	1.00	1.00	1.00	-0.008
Goerge et al., 2008	20	0.238	96227	1771669	17341.2	17341.2	0.50	1.00	1.00	1.00	0.119
Goerge et al., 2008	21	0.116	96227	1771669	5818.9	5818.9	0.50	1.00	1.00	1.00	0.058
Fletcher & Wolfe, 2009b	22	0.137	564	149	35.0	13.6	0.75	1.00	1.00	1.00	0.103
Hoffman, 2008	22	0.091	762	69	63.3	16.5	0.75	1.00	1.00	1.00	0.068
Boden et al., 2008	22	0.820	22	429	10.0	6.9	0.50	1.00	1.00	1.00	0.410
Angrist & Lavy, 1996	23	0.213	557	17238	539.2	539.2	1.00	1.00	1.00	1.00	0.213
Angrist & Lavy, 1996	23	0.148	500	541	259.1	259.1	1.00	1.00	1.00	1.00	0.148
Moore et al., 1997	23	0.245	77	199	24.2	24.2	0.50	1.00	1.00	1.00	0.123
Levine et al., 2007	23	0.320	451	354	84.0	84.0	1.00	1.00	1.00	1.00	0.320
Hoffman & Scher, 2008	24	-0.205	644	337	86.8	86.8	0.75	1.00	1.00	1.00	-0.154
Manlove et al., 2008	24	-0.150	221	461	73.8	73.8	0.50	1.00	1.00	1.00	-0.075
Francesconi, 2008	24	-0.314	85	1098	53.6	53.6	1.00	1.00	1.00	0.50	-0.157
Fletcher & Wolfe, 2009b	25	-0.241	563	148	71.1	71.1	0.75	1.00	1.00	1.00	-0.181
Fletcher, 2010	25	-0.192	233	2094	68.9	68.9	1.00	1.00	1.00	1.00	-0.192
Webbink et al., 2009	25	-0.065	77	77	25.4	25.4	1.00	1.00	1.00	1.00	-0.065
Hoffman, 2008	25	-0.096	453	41	25.3	25.3	0.75	1.00	1.00	1.00	-0.072
Pogarsky et al., 2003	26	0.145	228	457	151.9	151.9	0.75	1.00	1.00	1.00	0.109
Scher & Hoffman, 2008	26	0.268	465	1158	67.6	67.6	0.75	1.00	1.00	1.00	0.201
Ettner et al., 1997	27	-0.570	1327	3299	388.0	16.8	0.75	1.00	1.00	1.00	-0.428
Farahati et al., 2003	27	-0.255	74	438	32.8	11.5	0.75	1.00	1.00	1.00	-0.191
Savoca & Rosenheck, 2000	27	-0.624	315	1102	115.9	15.3	0.50	0.75	1.00	1.00	-0.234
Alexandre & French, 2001	27	-0.527	384	890	144.5	15.7	0.50	0.75	1.00	1.00	-0.198
Chatterji et al., 2007	27	-0.331	535	3538	302.8	16.6	0.50	1.00	1.00	1.00	-0.165
Cornwell et al., 2009	27	-0.059	1852	8790	735.0	17.2	0.75	1.00	1.00	1.00	-0.044
Ojeda et al., 2010	27	-0.881	2805	27418	1351.7	17.4	0.75	1.00	0.50	1.00	-0.330
Gibb et al., 2010	27	-0.251	238	713	60.9	13.6	0.75	1.00	1.00	1.00	-0.188
Cowell et al., 2009	27	-0.260	4749	28326	2718.1	17.5	0.50	1.00	1.00	1.00	-0.130
Alexandre et al., 2004	27	-0.204	1038	14371	145.7	15.7	0.50	1.00	1.00	1.00	-0.102
Frijters et al., 2010	27	-0.901	1716	5946	804.3	17.2	1.00	1.00	0.50	1.00	-0.451
Bruffaerts et al., 2009	27	-0.690	42	821	26.5	10.6	0.50	1.00	1.00	1.00	-0.345

Exhibit 70

Individual Effect Sizes Used in the Meta-Analysis of Each Topic											
		Study Results					Multiplicative Weights & Adjusted Effect Size				
Study (Date)	Topic Number	Un-adjusted effect size	Number in test condition group	Number in control group	Inverse variance weight-fixed effects	Inverse variance weight-random effects	Re-search design	General-izability of sample	Relevance of inde-pendent variable measure	Relevance of de-pendent variable measure	Adjusted effect size
Zhang et al., 2009	27	-0.251	4252	26040	1736.1	17.4	0.75	1.00	0.50	1.00	-0.094
Chatterji et al., 2009	27	-0.169	2536	9277	1081.7	17.3	0.50	1.00	1.00	1.00	-0.085
Tian et al., 2005	27	-0.150	459	5239	280.0	16.5	0.50	0.75	1.00	1.00	-0.056
Baldwin & Marcus, 2007	27	-0.577	1149	9675	456.4	16.9	0.50	1.00	1.00	1.00	-0.288
Jofre-Bonet et al., 2005	27	-0.457	13251	106632	7517.7	17.5	0.75	1.00	0.50	1.00	-0.171
WSIPP analysis	27	-0.197	1865	36202	1177.5	17.3	0.50	1.00	1.00	1.00	-0.098
Ettner et al., 1997	28	-0.212	1327	3299	942.2	316.0	0.75	1.00	1.00	1.00	-0.159
Marcotte & Wilcox-Gők, 2003	28	-0.164	1029	2402	718.5	286.1	0.75	1.00	1.00	1.00	-0.123
Frank & Gertler, 1991	28	-0.281	106	776	92.8	77.6	0.50	1.00	1.00	1.00	-0.141
French & Zarkin, 1998	28	-0.124	45	363	39.9	36.8	0.50	0.75	0.50	1.00	-0.023
Baldwin & Marcus, 2007	28	-0.051	1149	9675	1026.9	324.9	0.50	1.00	1.00	1.00	-0.025
Cseh, 2008	28	-0.039	1379	5657	1108.7	332.7	1.00	1.00	1.00	1.00	-0.039
Forbes et al., 2010	28	-0.042	5843	20959	4568.4	430.6	0.50	1.00	1.00	1.00	-0.021
Jofre-Bonet et al., 2005	28	-0.088	13251	106632	11782.2	456.9	0.75	1.00	0.50	1.00	-0.033
Chatterji et al., 2011	28	-0.052	911	3224	710.3	284.8	0.75	1.00	1.00	1.00	-0.039
Ettner et al., 1997	29	-0.328	454	4172	170.6	29.8	0.50	1.00	1.00	1.00	-0.164
Farahati et al., 2003	29	-0.255	74	438	32.8	17.2	0.75	1.00	1.00	1.00	-0.191
Savoca & Rosenheck, 2000	29	-0.602	79	1338	39.7	18.9	0.50	0.75	1.00	1.00	-0.226
Alexandre & French, 2001	29	-0.527	384	890	144.5	28.9	0.50	0.75	1.00	1.00	-0.198
Cornwell et al., 2009	29	-0.099	724	9917	336.8	32.6	0.75	1.00	1.00	1.00	-0.075
Gibb et al., 2010	29	-0.351	143	808	46.6	20.4	0.75	1.00	1.00	1.00	-0.263
Cowell et al., 2009	29	-0.270	1534	31541	987.0	34.8	0.50	1.00	1.00	1.00	-0.135
Chatterji et al., 2009	29	-0.310	1709	10104	861.7	34.7	0.50	1.00	1.00	1.00	-0.155
Tian et al., 2005	29	-0.150	459	5239	280.0	32.0	0.50	0.75	1.00	1.00	-0.056
Baldwin & Marcus, 2007	29	-0.687	703	10121	327.5	32.5	0.50	1.00	1.00	1.00	-0.343
Ettner et al., 1997	30	-0.086	454	4172	409.0	409.0	0.50	1.00	1.00	1.00	-0.043
Marcotte & Wilcox-Gők, 2003	30	0.008	483	2948	415.2	415.2	0.75	1.00	1.00	1.00	0.006
Baldwin & Marcus, 2007	30	-0.055	703	10121	657.3	657.3	0.50	1.00	1.00	1.00	-0.027
Cseh, 2008	30	-0.039	1379	5657	1108.7	1108.7	1.00	1.00	1.00	1.00	-0.039
Ettner et al., 1997	31	-0.087	562	4064	163.1	31.2	0.50	1.00	1.00	1.00	-0.043
Savoca & Rosenheck, 2000	31	-0.632	235	1182	97.1	27.6	0.50	0.75	1.00	1.00	-0.237
Cornwell et al., 2009	31	-0.032	1128	9513	476.1	35.6	0.75	1.00	1.00	1.00	-0.024
Gibb et al., 2010	31	-0.151	143	808	39.0	19.4	0.75	1.00	1.00	1.00	-0.114
Cowell et al., 2009	31	-0.116	2301	30774	1395.3	37.5	0.50	1.00	1.00	1.00	-0.058
Chatterji et al., 2009	31	-0.117	1168	10645	561.8	36.0	0.50	1.00	1.00	1.00	-0.058
Baldwin & Marcus, 2007	31	-0.583	294	10530	136.7	30.0	0.50	1.00	1.00	1.00	-0.292
Ettner et al., 1997	32	-0.029	562	4064	493.8	25.0	0.50	1.00	1.00	1.00	-0.014
Marcotte & Wilcox-Gők, 2003	32	-0.385	752	2679	579.7	25.2	0.75	1.00	1.00	1.00	-0.289
Baldwin & Marcus, 2007	32	-0.143	294	10530	285.9	24.1	0.50	1.00	1.00	1.00	-0.072
Fergusson & Lynskey, 1998	33	0.465	83	886	13.8	11.7	0.50	1.00	1.00	1.00	0.232
Satterfield et al., 2007	33	0.678	169	64	25.0	18.9	0.50	1.00	1.00	1.00	0.339
Fletcher & Wolfe, 2009a	33	0.388	691	2947	303.0	61.1	0.50	1.00	1.00	1.00	0.194
Copeland et al., 2007	33	0.339	125	1296	44.9	28.3	0.75	1.00	1.00	1.00	0.254
Fergusson et al., 2005	33	0.763	46	927	17.4	14.2	0.75	1.00	1.00	1.00	0.572
Bussing et al., 2010	33	0.684	94	163	10.3	9.1	0.75	1.00	1.00	0.50	0.256
Murray et al., 2010	33	0.360	1090	7296	427.4	64.9	0.75	1.00	1.00	1.00	0.270
Currie & Stabile, 2009	33	0.192	164	3056	105.5	44.4	0.75	1.00	1.00	1.00	0.144
Currie & Stabile, 2009	33	0.364	116	2162	74.8	37.8	0.75	1.00	1.00	1.00	0.273

Exhibit 70

Individual Effect Sizes Used in the Meta-Analysis of Each Topic											
			Study Results				Multiplicative Weights & Adjusted Effect Size				
Study (Date)	Topic Number	Un-adjusted effect size	Number in test condition group	Number in control group	Inverse variance weight-fixed effects	Inverse variance weight-random effects	Re-search design	General-izability of sample	Relevance of inde-pendent variable measure	Relevance of de-pendent variable measure	Adjusted effect size
Currie & Stabile, 2009	33	0.101	323	2903	197.6	55.2	0.75	1.00	1.00	1.00	0.075
Currie & Stabile, 2009	33	0.163	228	2050	135.5	48.9	0.75	1.00	1.00	1.00	0.122
Webbink et al., 2011	33	0.456	239	1899	62.3	34.3	1.00	1.00	1.00	1.00	0.456
Fletcher & Wolfe, 2008	34	-0.305	262	2645	93.8	62.2	0.50	1.00	1.00	1.00	-0.152
McLeod & Kaiser, 2004	34	-0.273	57	367	22.0	19.7	0.75	1.00	1.00	1.00	-0.205
Fergusson & Lynskey, 1998	34	-0.333	83	886	41.0	33.5	0.50	1.00	1.00	1.00	-0.167
Breslau et al., 2008	34	-0.555	380	5206	191.3	93.8	0.50	1.00	1.00	1.00	-0.278
Breslau et al., 2008	34	-0.322	486	5100	201.0	96.1	0.50	1.00	1.00	1.00	-0.161
Breslau et al., 2008	34	-0.389	704	4882	288.5	112.4	0.50	1.00	1.00	1.00	-0.194
Currie et al., 2010	34	-0.234	1739	48665	1090.5	157.5	1.00	1.00	1.00	1.00	-0.234
Galera et al., 2009	34	-0.369	71	643	22.6	20.1	0.75	1.00	1.00	1.00	-0.277
Galera et al., 2009	34	-0.438	71	643	21.0	18.8	0.75	1.00	1.00	1.00	-0.328
Currie & Stabile, 2009	34	-0.217	127	2355	55.5	42.7	0.75	1.00	1.00	1.00	-0.162
Currie & Stabile, 2009	34	-0.240	249	2237	104.1	66.5	0.75	1.00	1.00	1.00	-0.180
Currie & Stabile, 2009	34	-0.552	132	2466	67.1	49.2	0.75	1.00	1.00	1.00	-0.414
Currie & Stabile, 2009	34	-0.184	260	2339	90.7	60.8	0.75	1.00	1.00	1.00	-0.138
Breslau et al., 2011	34	-0.386	1513	28149	767.8	148.5	0.75	1.00	1.00	1.00	-0.289
Breslau et al., 2011	34	-0.309	2966	26696	1328.6	161.7	0.75	1.00	1.00	1.00	-0.232
Webbink et al., 2011	34	-0.233	216	1712	103.0	66.1	1.00	1.00	1.00	1.00	-0.233
Porche et al., 2011	34	-0.525	287	2245	129.6	76.1	0.50	1.00	1.00	1.00	-0.263
McLeod & Kaiser, 2004	35	-0.210	75	349	26.0	22.6	0.75	1.00	1.00	1.00	-0.158
Duchesne et al., 2008	35	-0.215	177	1640	93.6	60.9	0.75	1.00	0.50	1.00	-0.081
Breslau et al., 2008	35	-0.303	654	4932	254.8	103.5	0.50	1.00	1.00	1.00	-0.152
Breslau et al., 2008	35	-0.159	1782	3804	455.9	126.1	0.50	1.00	1.00	1.00	-0.079
Fletcher, 2010	35	-0.167	186	2141	55.2	41.9	1.00	1.00	1.00	1.00	-0.167
Fergusson & Woodward, 2002	35	-0.058	124	840	43.4	34.8	0.75	1.00	1.00	0.50	-0.022
Needham, 2009	35	-0.140	1564	12657	365.6	118.0	0.75	1.00	1.00	1.00	-0.105
Currie & Stabile, 2009	35	0.055	443	2043	129.7	74.4	0.75	1.00	1.00	1.00	0.041
Currie & Stabile, 2009	35	-0.029	463	2140	126.2	73.2	0.75	1.00	1.00	1.00	-0.022
Breslau et al., 2011	35	-0.054	7207	22455	2180.6	161.4	0.75	1.00	1.00	1.00	-0.041
Porche et al., 2011	35	0.018	368	2164	111.4	68.0	0.50	1.00	1.00	1.00	0.009
Fletcher & Wolfe, 2008	36	0.453	261	2643	54.0	53.8	0.50	1.00	0.50	1.00	0.113
Galera et al., 2009	36	0.597	163	1101	92.8	92.2	0.75	1.00	1.00	1.00	0.448
Currie & Stabile, 2009	36	0.347	359	3232	99.3	98.6	0.75	1.00	1.00	1.00	0.260
Currie & Stabile, 2009	36	0.468	582	5240	179.4	177.2	0.75	1.00	1.00	1.00	0.351
Currie & Stabile, 2009	37	-0.283	258	2318	230.9	31.9	0.75	1.00	1.00	1.00	-0.212
Currie & Stabile, 2009	37	-0.262	258	2318	231.0	32.0	0.75	1.00	1.00	1.00	-0.197
Currie & Stabile, 2009	37	-0.584	238	2142	211.0	31.5	0.75	1.00	1.00	1.00	-0.438
Fletcher & Wolfe, 2008	38	-0.305	262	2645	93.8	93.8	0.50	1.00	1.00	1.00	-0.152
Breslau et al., 2008	38	-0.322	486	5100	201.0	201.0	0.50	1.00	1.00	1.00	-0.161
Galera et al., 2009	38	-0.369	71	643	22.6	22.6	0.75	1.00	1.00	1.00	-0.277
Currie & Stabile, 2009	38	-0.240	249	2237	104.1	104.1	0.75	1.00	1.00	1.00	-0.180
Currie & Stabile, 2009	38	-0.184	260	2339	90.7	90.7	0.75	1.00	1.00	1.00	-0.138
Breslau et al., 2011	38	-0.309	2966	26696	1328.6	1328.6	0.75	1.00	1.00	1.00	-0.232
Satterfield et al., 2007	39	0.678	169	64	25.0	14.3	0.50	1.00	1.00	1.00	0.339
Fletcher & Wolfe, 2009a	39	0.388	691	2947	303.0	30.2	0.50	1.00	1.00	1.00	0.194
Bussing et al., 2010	39	0.684	94	163	10.3	7.9	0.75	1.00	1.00	0.50	0.256

Exhibit 70

Individual Effect Sizes Used in the Meta-Analysis of Each Topic											
			Study Results				Multiplicative Weights & Adjusted Effect Size				
Study (Date)	Topic Number	Un-adjusted effect size	Number in test condition group	Number in control group	Inverse variance weight-fixed effects	Inverse variance weight-random effects	Re-search design	General-izability of sample	Relevance of inde-pendent variable measure	Relevance of de-pendent variable measure	Adjusted effect size
Currie & Stabile, 2009	39	0.101	323	2903	197.6	28.7	0.75	1.00	1.00	1.00	0.075
Currie & Stabile, 2009	39	0.163	228	2050	135.5	26.9	0.75	1.00	1.00	1.00	0.122
Fergusson & Lynskey, 1998	40	-0.333	83	886	41.0	34.4	0.50	1.00	1.00	1.00	-0.167
Breslau et al., 2008	40	-0.555	380	5206	191.3	100.7	0.50	1.00	1.00	1.00	-0.278
Galera et al., 2009	40	-0.438	71	643	21.0	19.1	0.75	1.00	1.00	1.00	-0.328
Currie & Stabile, 2009	40	-0.217	127	2355	55.5	44.0	0.75	1.00	1.00	1.00	-0.162
Currie & Stabile, 2009	40	-0.552	132	2466	67.1	51.0	0.75	1.00	1.00	1.00	-0.414
Breslau et al., 2011	40	-0.386	1513	28149	767.8	166.5	0.75	1.00	1.00	1.00	-0.289
Porche et al., 2011	40	-0.525	287	2245	129.6	80.5	0.50	1.00	1.00	1.00	-0.263
Fergusson & Lynskey, 1998	41	0.465	83	886	13.8	13.6	0.50	1.00	1.00	1.00	0.232
Copeland et al., 2007	41	0.339	125	1296	44.9	42.7	0.75	1.00	1.00	1.00	0.254
Fergusson et al., 2005	41	0.763	46	927	17.4	17.1	0.75	1.00	1.00	1.00	0.572
Murray et al., 2010	41	0.360	1090	7296	427.4	286.6	0.75	1.00	1.00	1.00	0.270
Currie & Stabile, 2009	41	0.192	164	3056	105.5	94.1	0.75	1.00	1.00	1.00	0.144
Currie & Stabile, 2009	41	0.364	116	2162	74.8	68.8	0.75	1.00	1.00	1.00	0.273
Webbink et al., 2011	41	0.456	239	1899	62.3	58.1	1.00	1.00	1.00	1.00	0.456
Steadman et al., 1998	42	0.340	286	519	29.5	4.4	0.50	1.00	1.00	1.00	0.170
Fazel et al., 2010	42	0.938	2570	4059	426.6	5.1	0.50	1.00	1.00	1.00	0.469
Fazel et al., 2009	42	0.285	4680	8118	710.8	5.1	0.50	1.00	1.00	1.00	0.142

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Chapter 6: Methods to Access Risk and Uncertainty

The model described thus far in this Technical Manual produces single-point estimates of benefits and costs of different policy and program options. For example, the model may produce an expected bottom line of $2.35 of benefits for each dollar of costs for some particular program. A key question, however, is this: how risky is an estimate such as this? If we vary the inputs, how often will costs exceed benefits, rather than the other way around?

WSIPP's benefit-cost model includes many inputs and assumptions, and there is significant uncertainty around many of these factors. If the factors are varied, the model will produce different results. Therefore, it is important to test the model systematically for the riskiness inherent in the single point estimates.

We do this by employing a Monte Carlo simulation method where we run the model thousands of times, each time varying the inputs randomly after sampling from estimated ranges of uncertainty that surround the key inputs. We then record the results of each run of the model.

When this simulation process is complete, we then compute an expected net present value, an expected benefit-cost ratio, an expected internal rate of return, and a straightforward measure of investment risk: for any program, what percentage of the time can we expect benefits to exceed costs? That is, after running the model many times, what percentage of the time will the net present value of benefits be greater than zero (or the benefit-cost ratio be greater than one)?

6.1 Key Inputs Varied in the Monte Carlo Simulation Analysis

Potentially, all inputs to WSIPP's model could be varied. Since this would slow the model down considerably, we concentrate on estimating the risk and uncertainty around a set of key inputs to the model. Each simulation run draws randomly from estimated distributions around the following list of inputs.

Program Effect Sizes. As described in Chapters 2 and 3, the model is driven by the estimated effects of programs and policies on certain outcomes. We estimate these effect sizes meta-analytically, and that process produces a random effects standard error around the effect size. We model the adjusted mean effect size and the unadjusted standard error by sampling from a normal probability density distribution.

Linked Effect Sizes. Chapters 3 and 5 also describe how the model uses estimates of the way in which certain outcomes relate to the outcomes that we monetize in the benefit-cost model. These "linked" effect sizes are also estimated with standard errors and we use the adjusted mean effect sizes and the unadjusted standard errors to sample from a normal probability density distribution.

Discount Rates. The user can enter three different rates of discount (low, modal, and high) that are used evaluate future benefits and costs in present value terms. In a single run of the model, the modal discount rate is used. In simulation mode the discount rate is sampled from a triangular probability density distribution.

The mean or modal values for many other model inputs are varied in a Monte Carlo run and include the following:

- Program costs—triangular distribution
- Crime victimization costs—triangular distribution
- Criminal justice system costs—triangular distribution
- Criminal victimizations per conviction—triangular distribution
- Value of a statistical life—triangular distribution
- Deadweight cost of taxation—triangular distribution
- Labor market earnings from reduction in alcohol disorders—lognormal distribution
- Labor market earnings from reduction in regular tobacco smoking—lognormal distribution
- Labor market earnings from reduction in cannabis disorders—lognormal distribution
- Labor market earnings from reduction in non-cannabis illicit drug disorders—lognormal distribution
- Expected hospital costs per alcohol, illicit drug, or regular smoking event—triangular distribution
- Expected emergency department costs per alcohol, illicit drug, or regular smoking event—triangular distribution
- Expected public treatment costs per alcohol, illicit drug, or regular smoking event—triangular distribution
- Labor market earnings from one standard deviation increase in test scores—normal distribution
- Labor market earnings from an extra year of education—normal distribution
- Causal link between high school graduation and labor market earnings—triangular distribution

6.2 Computational Procedures to Carry Out the Simulation

Since the benefit-cost model is housed in Microsoft Excel® and uses Visual Basic for Applications® (VBA) to carry out computations, the simulation is also implemented within VBA using Excel's various statistical functions. First, a random number between zero and one is generated with Excel's *RANDBETWEEN* function with this procedure:

$$(6.1)\quad RandomDraw = RANDBETWEEN(1{,}999)/1000$$

Next, the distribution for the particular model input is sampled. For the normal distribution, Excel's normal distribution inverse function, *NORMINV,* is used to generate a draw for any outcome that is set to sample from a normal distribution. For example, an effect size for each run r in a simulation is generated with this procedure:

$$(6.2)\quad EffectSize_r = NORMINV(RandomDraw, EffectSizeMean, EffectSizeStandardError)$$

Other types of probability distributions are computed in a similar fashion.

Excel does not have a native probability function for a triangular distribution. Therefore, the following procedure is used to generate a draw from three triangular parameters supplied by the user. An example would be for the discount rate, *DISRATE*, variable included in simulation runs. VBA implements the following code to randomly draw a discount rate from a triangular distribution given Min, Mode, and Max parameters.

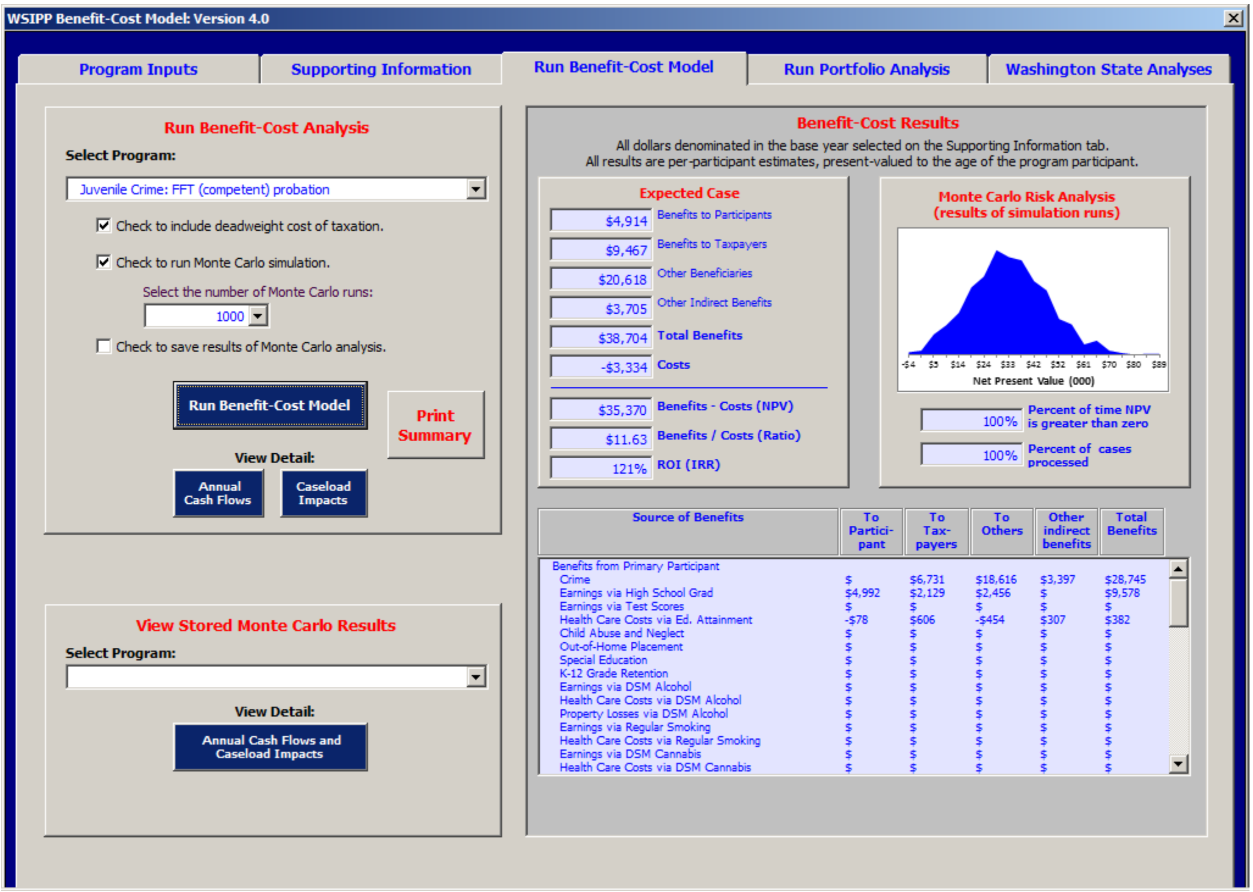
$$(6.3)\quad If\ RandomDraw < \frac{(Mode - Min)}{(Max - Min)}\ then\ DISRATE = Min + \sqrt{RandomDraw \times (Mode - Min) \times (Max - Min)}$$

$$(6.4)\quad If\ RandomDraw \geq \frac{(Mode - Min)}{(Max - Min)}\ then\ DISRATE = Max - \sqrt{(1 - RandomDraw) \times (Max - Mode) \times (Max - Min)}$$

Example

When the model is run for a program, and the user chooses to run the model in Monte Carlo mode, the user selects the number of runs to compute. Exhibit 71 is a screen shot of a program, Functional Family Therapy that was run in Monte Carlo mode. The user clicked Monte Carlo and selected 1000 runs. The Monte Carlo results are shown. The chart, for example, displays the distribution of the 1000 cases for the net present value (NPV) for the program.

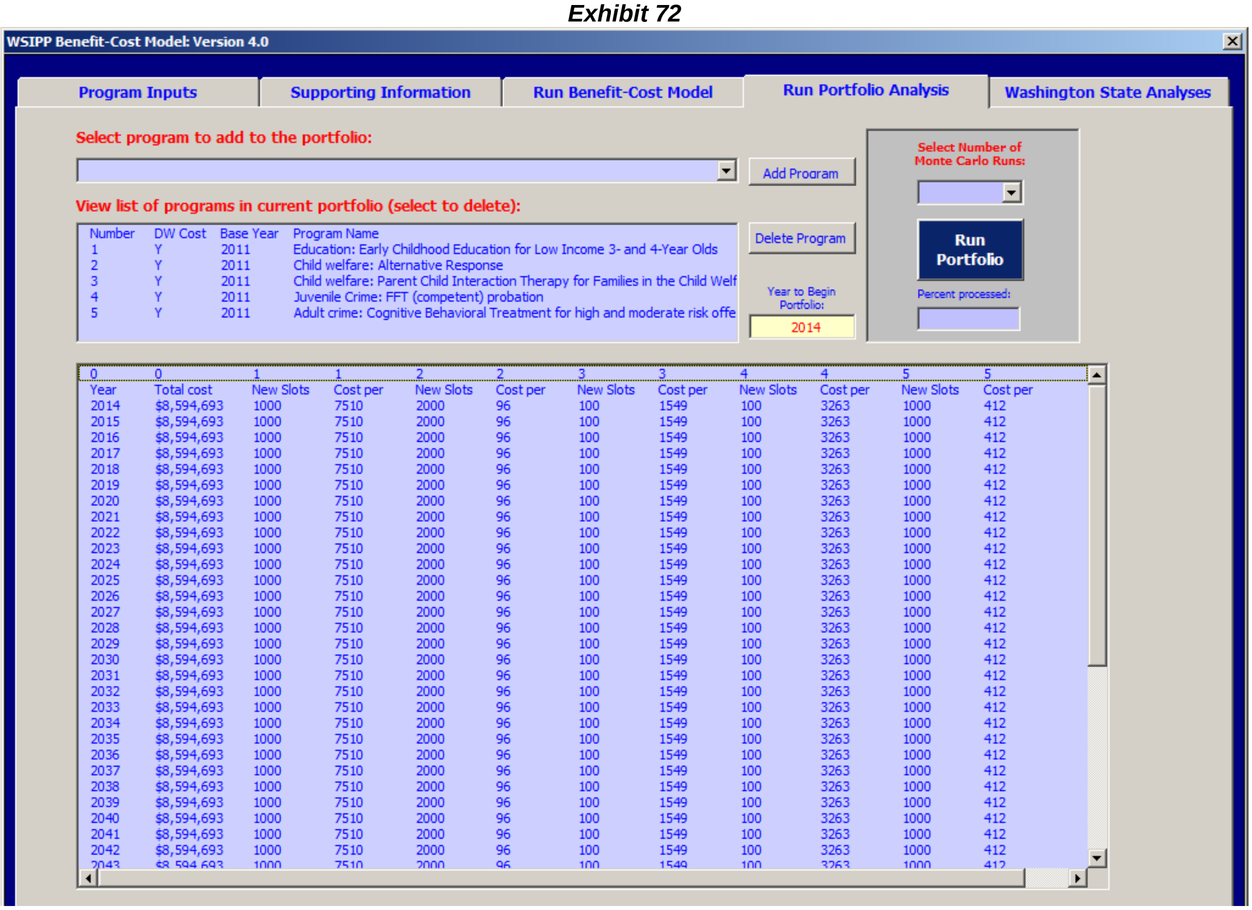
Exhibit 71


WSIPP Benefit-Cost Model: Version 4.0
Program Inputs
Supporting Information
Run Benefit-Cost Model
Run Portfolio Analysis
Washington State Analyses
Run Benefit-Cost Analysis
Select Program:
Juvenile Crime: FFT (competent) probation
Check to include deadweight cost of taxation.
Check to run Monte Carlo simulation.
Select the number of Monte Carlo runs:
1000
Check to save results of Monte Carlo analysis.
Run Benefit-Cost Model
Print Summary
View Detail:
Annual Cash Flows
Caseload Impacts
View Stored Monte Carlo Results
Select Program:
View Detail:
Annual Cash Flows and Caseload Impacts
Benefit-Cost Results
All dollars denominated in the base year selected on the Supporting Information tab.
All results are per-participant estimates, present-valued to the age of the program participant.
Expected Case
$4,914 Benefits to Participants
$9,467 Benefits to Taxpayers
$20,618 Other Beneficiaries
$3,705 Other Indirect Benefits
$38,704 Total Benefits
-$3,334 Costs
$35,370 Benefits - Costs (NPV)
$11.63 Benefits / Costs (Ratio)
121% ROI (IRR)
Monte Carlo Risk Analysis
(results of simulation runs)
Net Present Value (000)
100% Percent of time NPV is greater than zero
100% Percent of cases processed
Source of Benefits
To Partici-pant
To Tax-payers
To Others
Other indirect benefits
Total Benefits
Benefits from Primary Participant
Crime $ $6,731 $18,616 $3,397 $28,745
Earnings via High School Grad $4,992 $2,129 $2,456 $ $9,578
Earnings via Test Scores $ $ $ $ $
Health Care Costs via Ed. Attainment -$78 $606 -$454 $307 $382
Child Abuse and Neglect $ $ $ $ $
Out-of-Home Placement $ $ $ $ $
Special Education $ $ $ $ $
K-12 Grade Retention $ $ $ $ $
Earnings via DSM Alcohol $ $ $ $ $
Health Care Costs via DSM Alcohol $ $ $ $ $
Property Losses via DSM Alcohol $ $ $ $ $
Earnings via Regular Smoking $ $ $ $ $
Health Care Costs via Regular Smoking $ $ $ $ $
Earnings via DSM Cannabis $ $ $ $ $
Health Care Costs via DSM Cannabis $ $ $ $ $

WSIPP constructed an analytical portfolio tool for the Washington legislature to help identify evidence-based programming and policy options to improve outcomes for people in Washington State, as well as to reduce taxpayer and other societal costs. This portfolio tool is based on the sentencing tool developed by WSIPP in 2010[171] but has been expanded to include several new outcomes, not just those relevant to criminal justice.[172] The goal of the tool is to help users analyze the net effects of many kinds of evidence-based programs and policies, and examine the impact of user-defined combinations of programs and policies on costs, benefits, and caseloads. Specifically, the tool is designed to examine how changes in the mix of policy and programming strategies can affect, at the state level, the following: (1) the number victimizations from crime; (2) the number of prison beds needed; (3) the number of child abuse and neglect cases; (4) the number of out-of-home placements for children in child welfare; (5) the number of high school graduates; and (6) costs and benefits to society over time. The portfolio tool resides within WSIPP's benefit-cost model.

Evidence-Based Program Portfolio. The portfolio analysis screen, shown in Exhibit 72, displays the user-entered information about the number of slots and the total present-valued cost of each slot for each of the programs or policies the user has selected to include in a portfolio. In the box at the top of the screen, "Select program to add to the portfolio," the user adds previously stored programs to the portfolio to be analyzed with the tool. Exhibit 72 displays, as an example, a variety of programs, each for a different target population, to demonstrate the ability for a user to combine a unique set of programs and policies into a single portfolio. The user can also remove programs from the created portfolio by selecting a program in the "View list of programs in current portfolio (select to remove)" box, and then clicking on the "Remove Program" button. When running the application, the user selects the number of Monte Carlo simulation runs to conduct for the chosen portfolio and then clicks on the "Run Portfolio" button; a counter displays the percent of cases processed as the model runs.

Exhibit 72



Number	DW Cost	Base Year	Program Name
1	Y	2011	Education: Early Childhood Education for Low Income 3- and 4-Year Olds
2	Y	2011	Child welfare: Alternative Response
3	Y	2011	Child welfare: Parent Child Interaction Therapy for Families in the Child Welf
4	Y	2011	Juvenile Crime: FFT (competent) probation
5	Y	2011	Adult crime: Cognitive Behavioral Treatment for high and moderate risk offe

0	0	1	1	2	2	3	3	4	4	5	5
Year	Total cost	New Slots	Cost per	New Slots	Cost per	New Slots	Cost per	New Slots	Cost per	New Slots	Cost per
2014	$8,594,693	1000	7510	2000	96	100	1549	100	3263	1000	412
2015	$8,594,693	1000	7510	2000	96	100	1549	100	3263	1000	412
2016	$8,594,693	1000	7510	2000	96	100	1549	100	3263	1000	412
2017	$8,594,693	1000	7510	2000	96	100	1549	100	3263	1000	412
2018	$8,594,693	1000	7510	2000	96	100	1549	100	3263	1000	412
2019	$8,594,693	1000	7510	2000	96	100	1549	100	3263	1000	412
2020	$8,594,693	1000	7510	2000	96	100	1549	100	3263	1000	412
2021	$8,594,693	1000	7510	2000	96	100	1549	100	3263	1000	412
2022	$8,594,693	1000	7510	2000	96	100	1549	100	3263	1000	412
2023	$8,594,693	1000	7510	2000	96	100	1549	100	3263	1000	412
2024	$8,594,693	1000	7510	2000	96	100	1549	100	3263	1000	412
2025	$8,594,693	1000	7510	2000	96	100	1549	100	3263	1000	412
2026	$8,594,693	1000	7510	2000	96	100	1549	100	3263	1000	412
2027	$8,594,693	1000	7510	2000	96	100	1549	100	3263	1000	412
2028	$8,594,693	1000	7510	2000	96	100	1549	100	3263	1000	412
2029	$8,594,693	1000	7510	2000	96	100	1549	100	3263	1000	412
2030	$8,594,693	1000	7510	2000	96	100	1549	100	3263	1000	412
2031	$8,594,693	1000	7510	2000	96	100	1549	100	3263	1000	412
2032	$8,594,693	1000	7510	2000	96	100	1549	100	3263	1000	412
2033	$8,594,693	1000	7510	2000	96	100	1549	100	3263	1000	412
2034	$8,594,693	1000	7510	2000	96	100	1549	100	3263	1000	412
2035	$8,594,693	1000	7510	2000	96	100	1549	100	3263	1000	412
2036	$8,594,693	1000	7510	2000	96	100	1549	100	3263	1000	412
2037	$8,594,693	1000	7510	2000	96	100	1549	100	3263	1000	412
2038	$8,594,693	1000	7510	2000	96	100	1549	100	3263	1000	412
2039	$8,594,693	1000	7510	2000	96	100	1549	100	3263	1000	412
2040	$8,594,693	1000	7510	2000	96	100	1549	100	3263	1000	412
2041	$8,594,693	1000	7510	2000	96	100	1549	100	3263	1000	412
2042	$8,594,693	1000	7510	2000	96	100	1549	100	3263	1000	412
2043	$8,594,693	1000	7510	2000	96	100	1549	100	3263	1000	412

[171] Aos, S. & Drake, E. (2010). *WSIPP's benefit-cost tool for states: Examining policy options in sentencing and corrections*. (Document No. 10-08-1201). Olympia: Washington State Institute for Public Policy.

[172] The high school graduation portion of the portfolio model was funded by the MacArthur Foundation, and the child welfare component was funded by the Pew Charitable Trusts.

The WSIPP portfolio tool implements a three-step computational process:

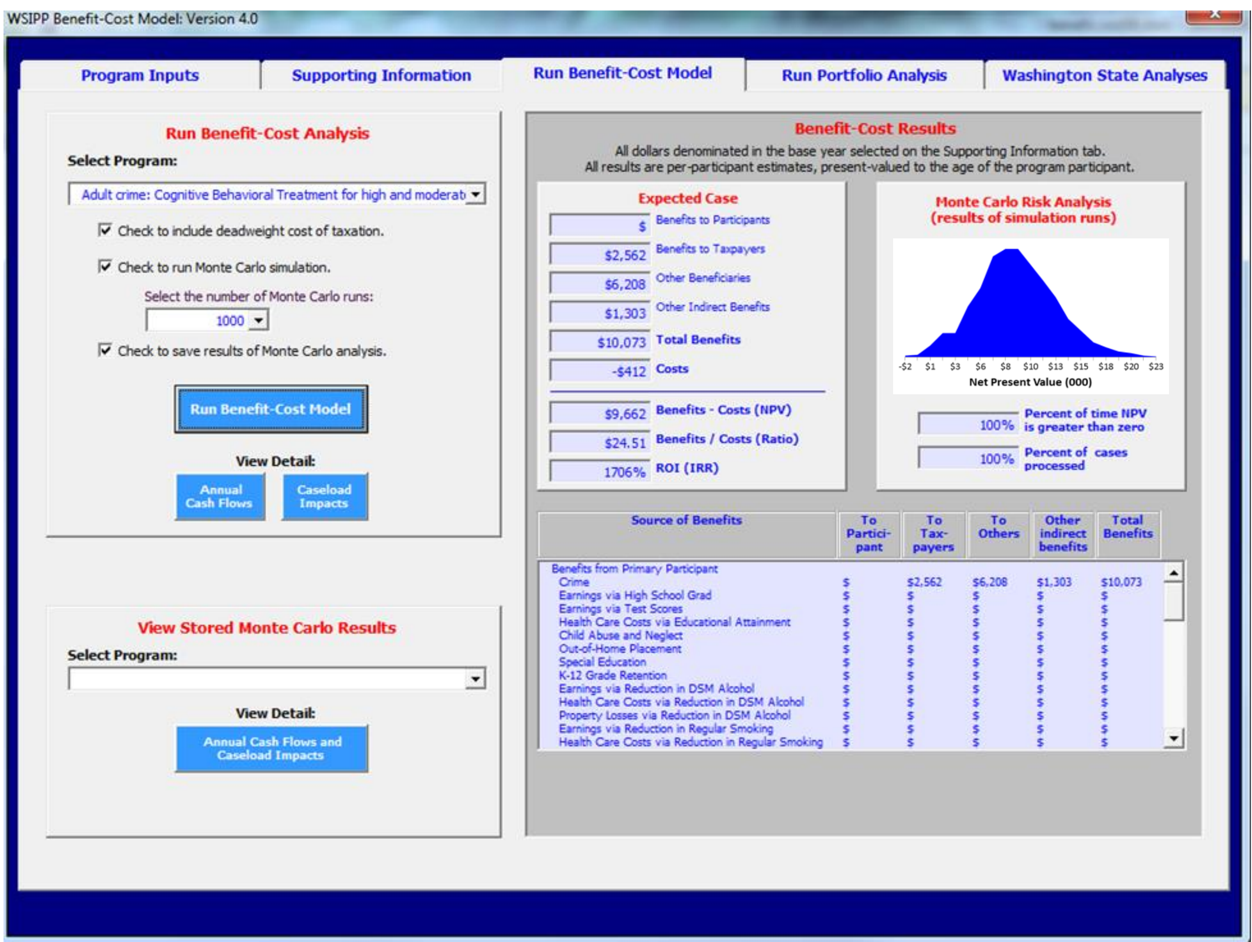
1. First, using a Monte Carlo approach, the user runs each program to be included in a portfolio to estimate the program's expected benefits and costs and of their ability to affect outcomes and related taxpayer and societal savings;
2. Results of an overall portfolio of programming and policy resources are tallied; and
3. Sensitivity analysis is conducted by simulating uncertainty in the analysis using a Monte Carlo approach.

7.1 Estimating the Expected Benefits and Costs of Programs and Policies

Any program or policy in the WSIPP benefit-cost model can be run using a Monte Carlo approach. On the main analysis screen (see Exhibit 73 below), when a user runs a single program in Monte Carlo mode, the user can also choose to save those results for future inclusion in a portfolio analysis. This "save" option stores two types of information crucial to the portfolio analysis. First, the mean, per-participant benefits and costs from the user-selected number of Monte Carlo simulation runs are stored for each year in a participant's projected lifetime. The standard deviations from these means are also stored. Second, the mean per-participant "person counts" and their standard deviations are also stored for each year in a participant's projected lifetime. The person counts currently have five types: projected per-participant changes in prison average daily population, crime victimizations, high school graduates, child abuse and neglect cases, and out-of-home placements in child welfare. These counts underlie the benefit and cost calculations in the crime, child welfare, and high school graduation areas, detailed in Chapters 4.1, 4.2, 4.3, and 4.7.

Key parameters that are allowed to vary in the individual program-level Monte Carlo simulations are described in detail in Chapter 6.1.

Exhibit 73



7.2 Preparing Programs and Policies for Portfolio Analysis

In addition to the results of a Monte Carlo simulation, the portfolio analysis also requires several other pieces of information for each program or policy. Exhibit 74 displays the input screen for required portfolio inputs. The user must fill out this input screen for each program or policy option they wish to include in a portfolio analysis. The information is stored alongside the outputs from the Monte Carlo simulation. The blue display box on the left side of the screen allows the user to input varying assumptions about the number of slots that will be funded and the annual per-participant cost.

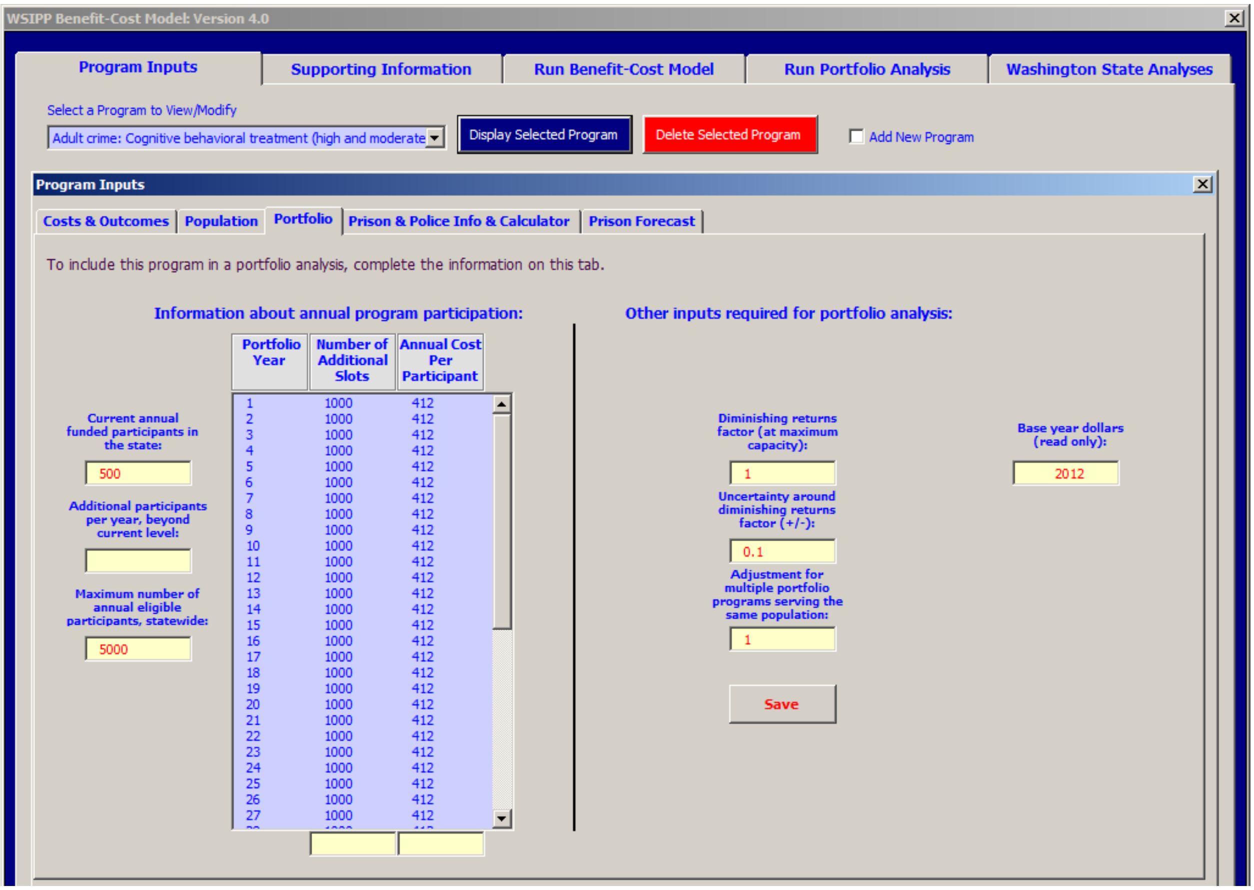
The cost is expressed in present-value terms; the model automatically populates the "annual cost per participant" column with costs entered on the Program Inputs, Costs & Outcomes tab, present valued to base year dollars. However, if there is a reason to believe that the actual costs of implementation will differ,[173] the user can manually overwrite the automatically generated costs, and vary them year by year if needed.

One important concept for long term portfolio analysis is that of diminishing returns. This is the precept that, as a program serves more and more of its eligible population (that is, as it reaches market saturation), the effectiveness of the program for each new participant may be reduced. To allow the user to model this, the user is required to input three pieces of information: the current annual funded participants in each program (500 in example shown in Exhibit 74, below), the maximum number of annual eligible participants (5000 in the example), and how effective the program is expected to be at maximum capacity (the "diminishing returns factor," expressed as a decimal between zero and one where 1 means that there is as effective at the last eligible program participant as the first, while zero mean the program is completely ineffective when it serves at the maximum level). The user is also able to estimate the variability expressed as percentage of the chosen diminishing returns factor; the variability is modeled with a triangular distribution in the portfolio Monte Carlo simulation.

Finally, the user is also required to enter an adjustment for each specific program, given what he or she knows about the mix of programs and policies in a given portfolio scenario. In the example shown on the screen shot below, the adjustment is set to one. However, if the user had a portfolio which included several programs for high-to-moderate risk adult offenders (for example), the user might enter a lower or higher number to reflect the fact that individuals might receive more than one treatment, and those treatments may not have fully independent effects on outcomes. A number less than one would indicate that if a participant participates in several programs, the combined effect will be less that the simple addition of the two individual program effects, while a number greater than one would indicate that the combined effects of multiple programs would be greater than the individual sum of each program's contributions.

[173] For example, the user might expect lower costs initially because the program is already being run at scale in the state and the infrastructure already exists to add participants efficiently. Conversely, the user may expect higher initial costs because the program has never been run before in the state and will require extra investment at the front end to hire and train staff and secure space.

Exhibit 74



Portfolio Year	Number of Additional Slots	Annual Cost Per Participant
1	1000	412
2	1000	412
3	1000	412
4	1000	412
5	1000	412
6	1000	412
7	1000	412
8	1000	412
9	1000	412
10	1000	412
11	1000	412
12	1000	412
13	1000	412
14	1000	412
15	1000	412
16	1000	412
17	1000	412
18	1000	412
19	1000	412
20	1000	412
21	1000	412
22	1000	412
23	1000	412
24	1000	412
25	1000	412
26	1000	412
27	1000	412

7.3 Combining Results of a Portfolio of Programs and Policies

At this stage, the user has already run the programs or policies that he or she wishes to include in a portfolio analysis through the Monte Carlo simulation process and saved the results, as displayed in Exhibit 73. The user has also provided the necessary information about each program, shown in Exhibit 74.

The user can then select any of the analyzed programs or policies to include in a portfolio scenario (see Exhibit 72).

Using the previously stored results for the programs selected for the portfolio, the model conducts a simple summation over time. For all programs in a portfolio, N, and for each follow-up year of investment i, the total change expected in a "person" outcome (e.g., prison beds, crime victimizations, child abuse and neglect cases, out-of-home placements) is the sum of the change in that person outcome for program p in investment year i, from follow up year 1 to i, multiplied by three factors: the number of slots funded in the follow up year for that program ($AddSlots_{py}$), the multiple-program adjustment factor for the program ($AdjFactor_p$), and by the diminishing returns factor computed for that year ($DRFactor_{py}$).

$$(7.1) \quad \Delta Person_i = \sum_{p=1}^{N} \sum_{y=1}^{i} \Delta Person_{p(i-y+1)} * AddSlots_{py} * AdjFactor_p * DRFactor_{py}$$

We use Microsoft Excel's native future value (FV) and rate (RATE) functions to compute the diminishing returns multiplier ($DRFactor_y$) to adjust the expected effectiveness of a program, depending on how close the additional slots specified in the portfolio will bring us to maximum capacity. This factor may vary year to year, depending on the user-specified number of additional slots to be added.

DR is the expected level of effectiveness when the program reaches maximum capacity
Current is the number of annual slots currently being funded statewide.
AddSlots is the number of additional slots to be funded in year y.
MaxCap is the maximum number of people in the state who meet the eligibility requirements for the program.

$$(7.2)\quad DRFactor_y = \frac{FV\left(RATE(99,0,-1,DR),\left(\frac{(Current + AddSlots_y)}{MaxCap} * 100,0,-1\right)\right) + FV\left(RATE(99,0,-1,DR),\left(\frac{Current}{MaxCap} * 100,0,-1\right)\right)}{2}$$

7.4 Risk Analysis

Analyzing these program and policy investment scenarios involves a substantial amount of risk. While there is an increasingly strong evidentiary base of knowledge about what works to improve outcomes, there remains a considerable level of variation in particular estimates. To reflect this uncertainty, the third step in our portfolio modeling approach is designed to estimate the riskiness of any combination of policy options.

As with any investment decision, a risk-adverse investor typically wants to know the expected gain of an investment along with a measure of the risk that the investment strategy could produce an undesired result. WSIPP's tool is structured to provide this type of investment information. The bottom-line investment statistics that the WSIPP tool produces include the expected change in taxpayer spending for a portfolio of policy options, along with the risk that the mix of options could lead to more crime, not less.

We estimate the known variability surrounding many of the inputs to the portfolio tool. Expected-value results of individual programs and policies are stored, using the variable parameters described in Chapter 6.1. We implement a Monte Carlo simulation approach in Excel, in which each time a scenario is run (the user selects the number of simulations to run), the tool draws randomly from the user-specified or model-generated probability distributions for the variables shown in the following table.

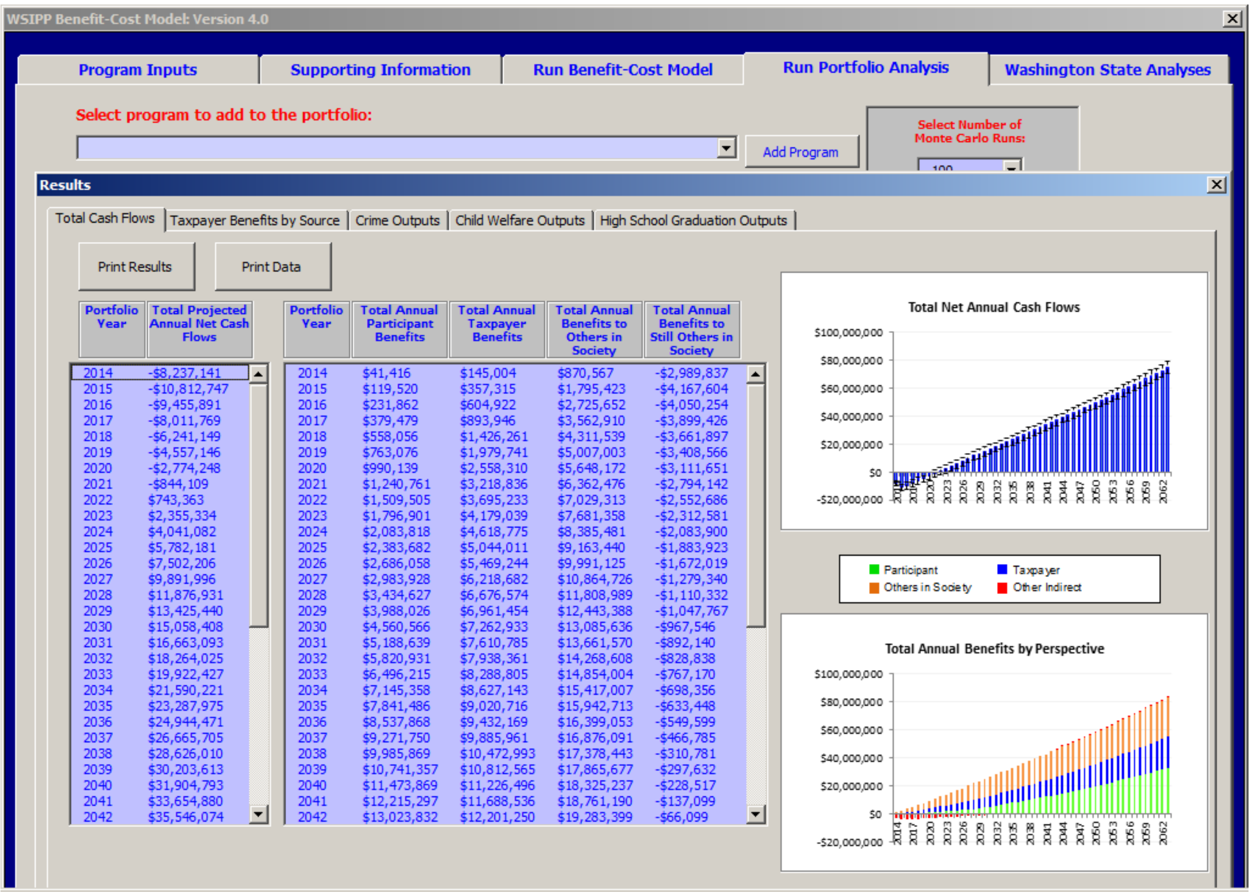
Exhibit 75
Parameters Allowed to Vary in Monte Carlo Simulation of a Portfolio Scenario

Portfolio-Level Parameter Allowed to Vary	Type of Probability Distribution
Portfolio-Level Variation	
Diminishing returns factor*	Triangular
Program Costs	Normal
Program Benefits	Normal
Change in Crime Victimizations	Normal
Change in Prison ADP	Normal
Change in High School Graduates	Normal
Change in Child Abuse and Neglect Cases	Normal
Change in Child Welfare Out-of-Home Placements	Normal

* The specific parameters for this distribution are selected by the user.

Exhibits 76 to 80 illustrate the output for a hypothetical portfolio scenario. Included in the output forms are total cash flows, detailed by perspective and by budget area. In addition, we display expected values for changes in prison beds, crime victimizations, child abuse and neglect cases, out-of-home placements, and high school graduates.

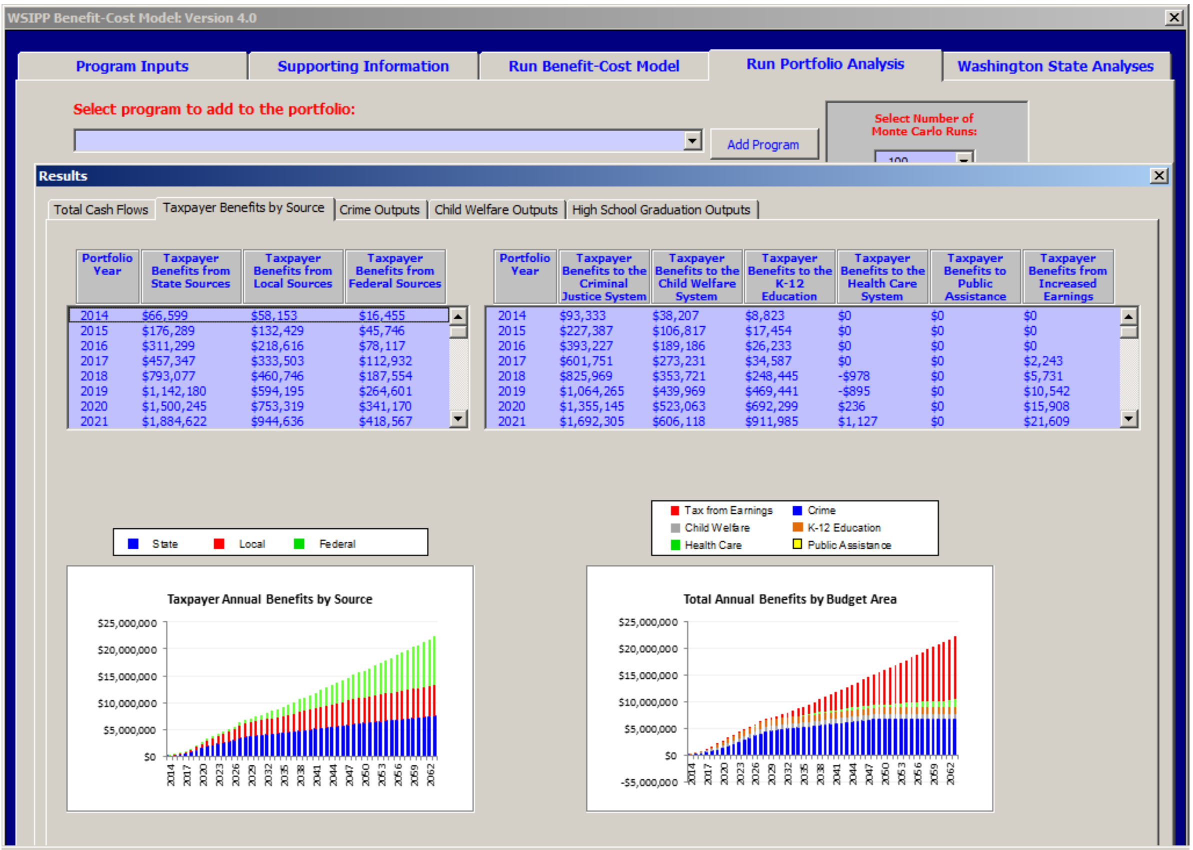
Exhibit 76



Portfolio Year	Total Projected Annual Net Cash Flows
2014	-$8,237,141
2015	-$10,812,747
2016	-$9,455,891
2017	-$8,011,769
2018	-$6,241,149
2019	-$4,557,146
2020	-$2,774,248
2021	-$844,109
2022	$743,363
2023	$2,355,334
2024	$4,041,082
2025	$5,782,181
2026	$7,502,206
2027	$9,891,996
2028	$11,876,931
2029	$13,425,440
2030	$15,058,408
2031	$16,663,093
2032	$18,264,025
2033	$19,922,427
2034	$21,590,221
2035	$23,287,975
2036	$24,944,471
2037	$26,665,705
2038	$28,626,010
2039	$30,203,613
2040	$31,904,793
2041	$33,654,880
2042	$35,546,074

Portfolio Year	Total Annual Participant Benefits	Total Annual Taxpayer Benefits	Total Annual Benefits to Others in Society	Total Annual Benefits to Still Others in Society
2014	$41,416	$145,004	$870,567	-$2,989,837
2015	$119,520	$357,315	$1,795,423	-$4,167,604
2016	$231,862	$604,922	$2,725,652	-$4,050,254
2017	$379,479	$893,946	$3,562,910	-$3,899,426
2018	$558,056	$1,426,261	$4,311,539	-$3,661,897
2019	$763,076	$1,979,741	$5,007,003	-$3,408,566
2020	$990,139	$2,558,310	$5,648,172	-$3,111,651
2021	$1,240,761	$3,218,836	$6,362,476	-$2,794,142
2022	$1,509,505	$3,695,233	$7,029,313	-$2,552,686
2023	$1,796,901	$4,179,039	$7,681,358	-$2,312,581
2024	$2,083,818	$4,618,775	$8,385,481	-$2,083,900
2025	$2,383,682	$5,044,011	$9,163,440	-$1,883,923
2026	$2,686,058	$5,469,244	$9,991,125	-$1,672,019
2027	$2,983,928	$6,218,682	$10,864,726	-$1,279,340
2028	$3,434,627	$6,676,574	$11,808,989	-$1,110,332
2029	$3,988,026	$6,961,454	$12,443,388	-$1,047,767
2030	$4,560,566	$7,262,933	$13,085,636	-$967,546
2031	$5,188,639	$7,610,785	$13,661,570	-$892,140
2032	$5,820,931	$7,938,361	$14,268,608	-$828,838
2033	$6,496,215	$8,288,805	$14,854,004	-$767,170
2034	$7,145,358	$8,627,143	$15,417,007	-$698,356
2035	$7,841,486	$9,020,716	$15,942,713	-$633,448
2036	$8,537,868	$9,432,169	$16,399,053	-$549,599
2037	$9,271,750	$9,885,961	$16,876,091	-$466,785
2038	$9,985,869	$10,472,993	$17,378,443	-$310,781
2039	$10,741,357	$10,812,565	$17,865,677	-$297,632
2040	$11,473,869	$11,226,496	$18,325,237	-$228,517
2041	$12,215,297	$11,688,536	$18,761,190	-$137,099
2042	$13,023,832	$12,201,250	$19,283,399	-$66,099

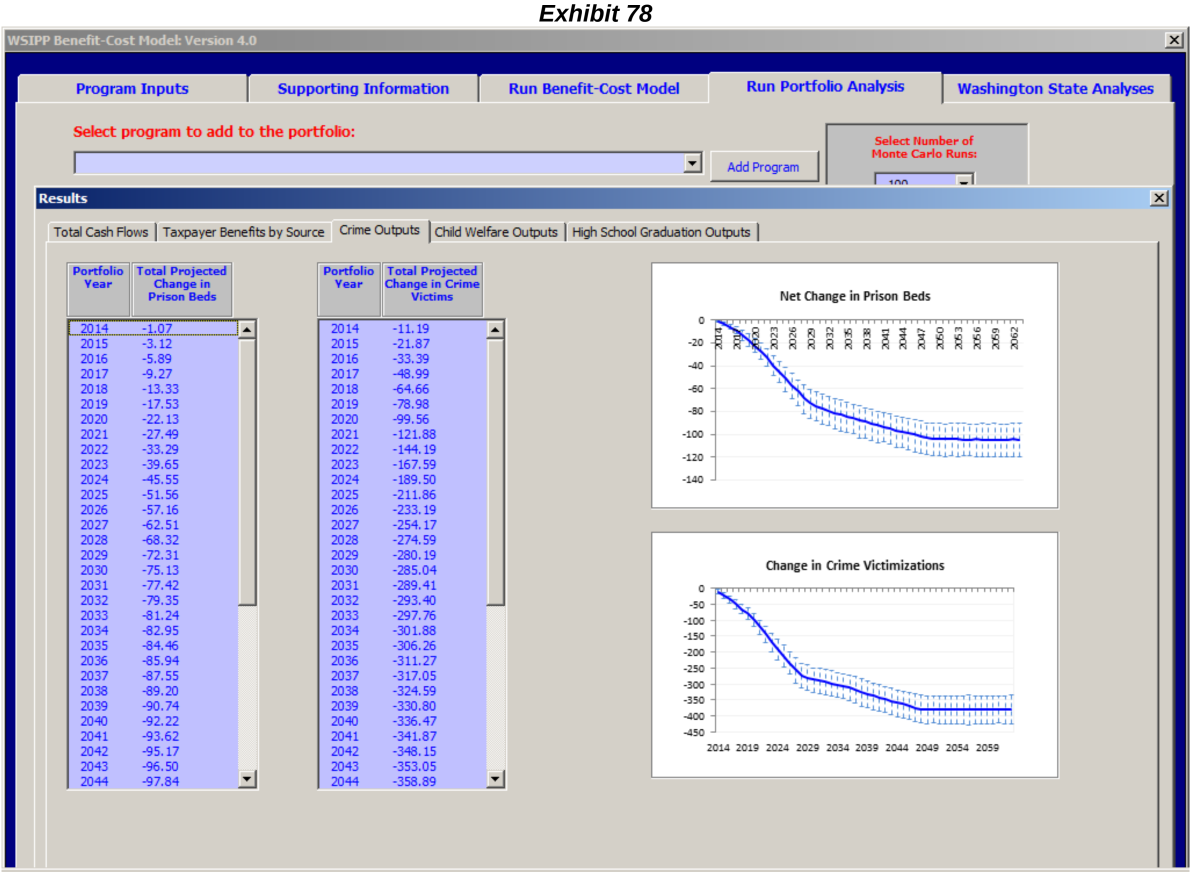
Exhibit 77



Portfolio Year	Taxpayer Benefits from State Sources	Taxpayer Benefits from Local Sources	Taxpayer Benefits from Federal Sources
2014	$66,599	$58,153	$16,455
2015	$176,289	$132,429	$45,746
2016	$311,299	$218,616	$78,117
2017	$457,347	$333,503	$112,932
2018	$793,077	$460,746	$187,554
2019	$1,142,180	$594,195	$264,601
2020	$1,500,245	$753,319	$341,170
2021	$1,884,622	$944,636	$418,567

Portfolio Year	Taxpayer Benefits to the Criminal Justice System	Taxpayer Benefits to the Child Welfare System	Taxpayer Benefits to the K-12 Education	Taxpayer Benefits to the Health Care System	Taxpayer Benefits to Public Assistance	Taxpayer Benefits from Increased Earnings
2014	$93,333	$38,207	$8,823	$0	$0	$0
2015	$227,387	$106,817	$17,454	$0	$0	$0
2016	$393,227	$189,186	$26,233	$0	$0	$0
2017	$601,751	$273,231	$34,587	$0	$0	$2,243
2018	$825,969	$353,721	$248,445	-$978	$0	$5,731
2019	$1,064,265	$439,969	$469,441	-$895	$0	$10,542
2020	$1,355,145	$523,063	$692,299	$236	$0	$15,908
2021	$1,692,305	$606,118	$911,985	$1,127	$0	$21,609

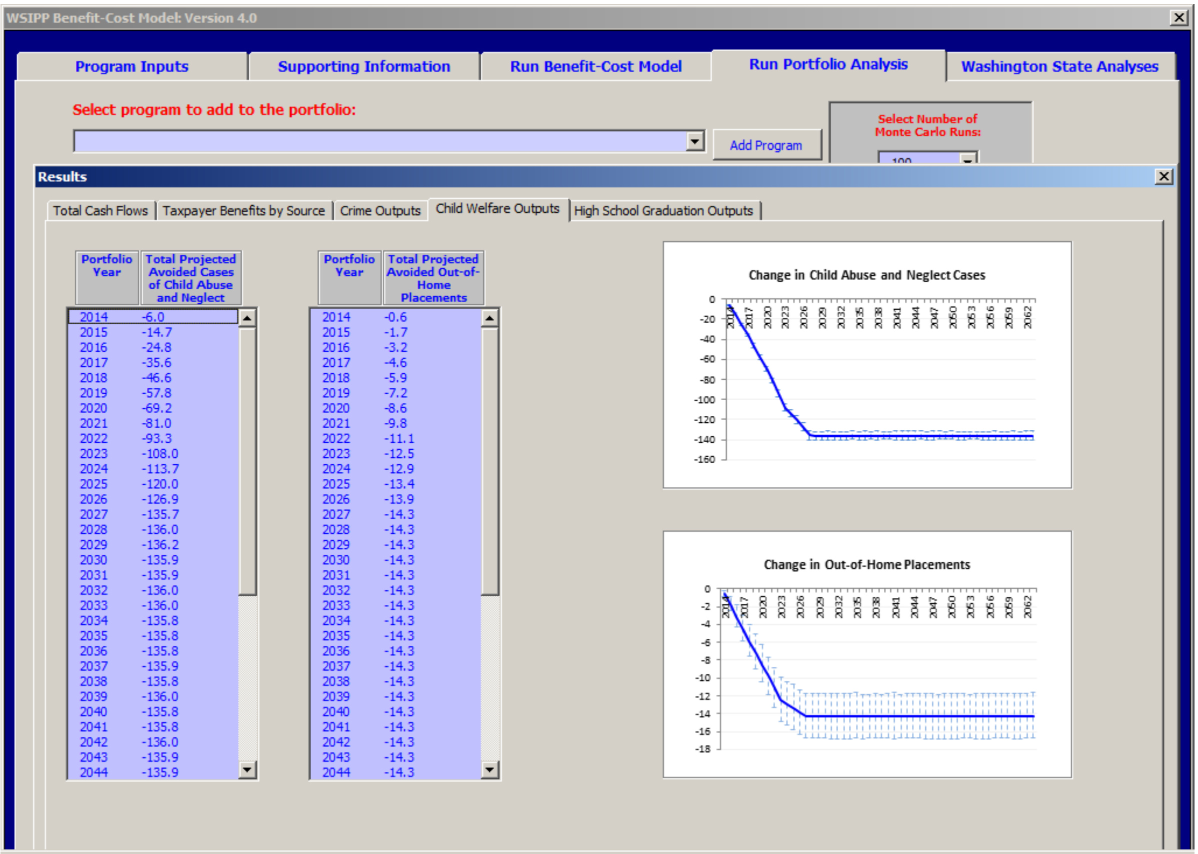
Exhibit 78



Portfolio Year	Total Projected Change in Prison Beds
2014	-1.07
2015	-3.12
2016	-5.89
2017	-9.27
2018	-13.33
2019	-17.53
2020	-22.13
2021	-27.49
2022	-33.29
2023	-39.65
2024	-45.55
2025	-51.56
2026	-57.16
2027	-62.51
2028	-68.32
2029	-72.31
2030	-75.13
2031	-77.42
2032	-79.35
2033	-81.24
2034	-82.95
2035	-84.46
2036	-85.94
2037	-87.55
2038	-89.20
2039	-90.74
2040	-92.22
2041	-93.62
2042	-95.17
2043	-96.50
2044	-97.84

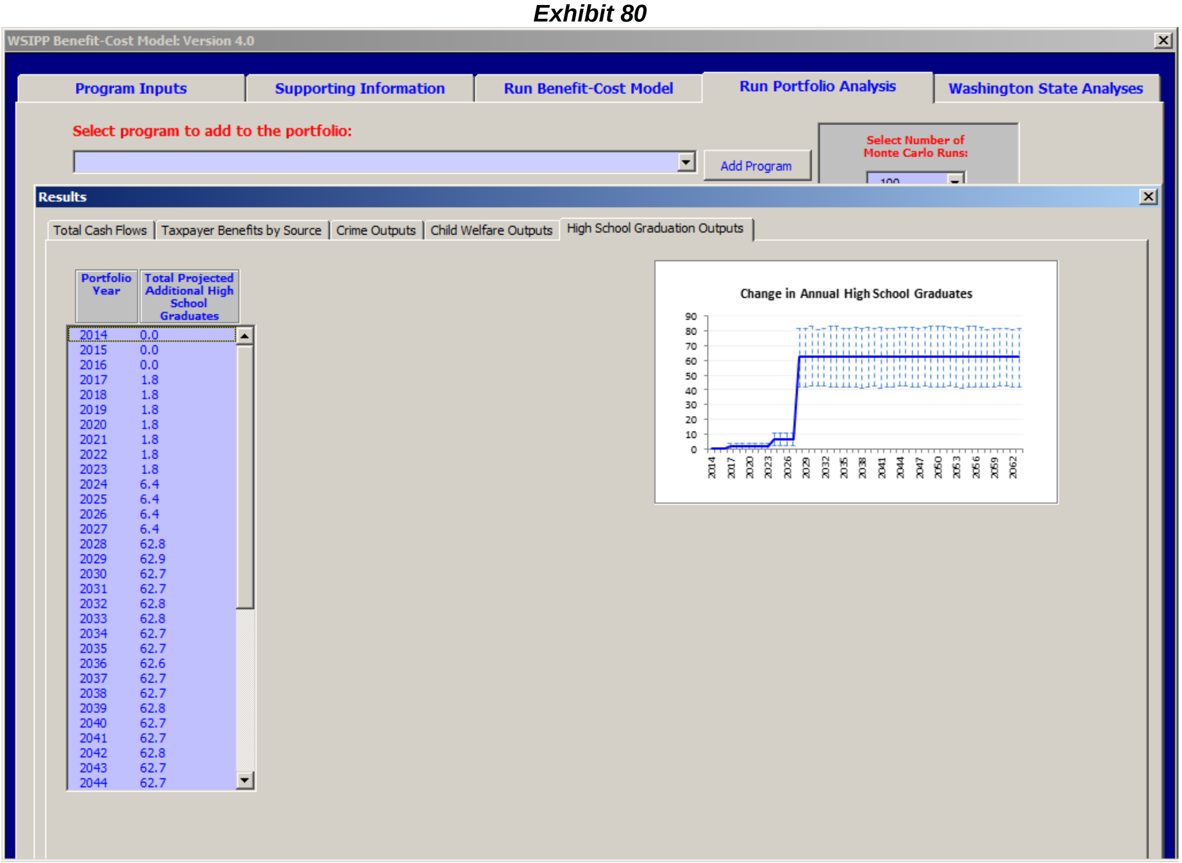
Portfolio Year	Total Projected Change in Crime Victims
2014	-11.19
2015	-21.87
2016	-33.39
2017	-48.99
2018	-64.66
2019	-78.98
2020	-99.56
2021	-121.88
2022	-144.19
2023	-167.59
2024	-189.50
2025	-211.86
2026	-233.19
2027	-254.17
2028	-274.59
2029	-280.19
2030	-285.04
2031	-289.41
2032	-293.40
2033	-297.76
2034	-301.88
2035	-306.26
2036	-311.27
2037	-317.05
2038	-324.59
2039	-330.80
2040	-336.47
2041	-341.87
2042	-348.15
2043	-353.05
2044	-358.89

Exhibit 79



Portfolio Year	Total Projected Avoided Cases of Child Abuse and Neglect	Portfolio Year	Total Projected Avoided Out-of-Home Placements
2014	-6.0	2014	-0.6
2015	-14.7	2015	-1.7
2016	-24.8	2016	-3.2
2017	-35.6	2017	-4.6
2018	-46.6	2018	-5.9
2019	-57.8	2019	-7.2
2020	-69.2	2020	-8.6
2021	-81.0	2021	-9.8
2022	-93.3	2022	-11.1
2023	-108.0	2023	-12.5
2024	-113.7	2024	-12.9
2025	-120.0	2025	-13.4
2026	-126.9	2026	-13.9
2027	-135.7	2027	-14.3
2028	-136.0	2028	-14.3
2029	-136.2	2029	-14.3
2030	-135.9	2030	-14.3
2031	-135.9	2031	-14.3
2032	-136.0	2032	-14.3
2033	-136.0	2033	-14.3
2034	-135.8	2034	-14.3
2035	-135.8	2035	-14.3
2036	-135.8	2036	-14.3
2037	-135.9	2037	-14.3
2038	-135.8	2038	-14.3
2039	-136.0	2039	-14.3
2040	-135.8	2040	-14.3
2041	-135.8	2041	-14.3
2042	-136.0	2042	-14.3
2043	-135.9	2043	-14.3
2044	-135.9	2044	-14.3

Exhibit 80



Portfolio Year	Total Projected Additional High School Graduates
2014	0.0
2015	0.0
2016	0.0
2017	1.8
2018	1.8
2019	1.8
2020	1.8
2021	1.8
2022	1.8
2023	1.8
2024	6.4
2025	6.4
2026	6.4
2027	6.4
2028	62.8
2029	62.9
2030	62.7
2031	62.7
2032	62.8
2033	62.8
2034	62.7
2035	62.7
2036	62.6
2037	62.7
2038	62.7
2039	62.8
2040	62.7
2041	62.7
2042	62.8
2043	62.7
2044	62.7